# Behavioral Decision Making for Sustainable Development

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# Abstract

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Human decisions are simultaneously determined by economic incentives and psychological motivations. Based upon this fundamental assumption, I compose three interdisciplinary studies which analyze individual, collective and governmental actions at multiple levels of aggregation, and how they in turn lead to various economic and psychological outcomes. In the first study[1], I explore the key predictors of the level of compliance to social distancing and mask wearing in the United states by aggregating interdisciplinary datasets and applying multi-level analysis. I use a behavioral model to classify the determinants of compliance to COVID-19 response measures into economic incentives and psychological motivations and show that the former would have an increasing marginal effect on working hours. Empirically, I show that (a) economic vulnerability was the key predictor of failure of social distancing in 2020, even taking partisanship into account. (b) mask wearing was more politicized than social distancing, and in Fall (close to the elections), Republican partisanship was the only dominant indicator of noncompliance of mask wearing. In the second study[2], we use a coordination game model to discuss the dynamics of Non-Pharmaceutical Interventions (NPIs) on COVID-19 in the United States. We use a theoretical model to justify that there exist social reinforcement effects between policies in US states, i.e. the implementation of an NPI in a state would increase the possibility that others follow suit. Under certain conditions, if enough states engage in NPIs, they will tip others that have not yet done so to follow suit and thus


[1]Single first author and joint correspondence author, with many minor co-authors

[2]Joint author, with Geoffrey Heal, Howard Kunreuther and Lu Liu,

shift the Nash equilibrium to the greatest one (all states follow). Then, we show that there can be equilibria where states with different political leanings adopt different strategies when politics is a determinant of the interaction intensity. Empirically, we use a random utility model (RUM) to test it in reality with Probit and Logit regressions, and find robust evidence that inter-state social reinforcement is important and that equilibria can be tipped in mask wearing, and slightly weaker confirmation for social distancing. In the last study[3], I explore how personality traits in China are different from the traditional Five Factor model by a large twin dataset in Yunnan Province. I find robust evidence about personality structures, formation and impacts in China and state three findings: (1) Personality traits in China seem to have a significance deviation from the well-accepted Five Factor Model. Instead, it has two general factors, relying on whether the item is positive or negative in tone. Positive factors include *Social Desirability, Extraversion and Openness*; negative factors include *Disorderliness, Neuroticism and Introversion*. (2) The genetic heritability of personality traits in China is significantly lower than that measured in the Western countries. For some traits, such as Social Desirability and Disorderliness, the genetic effect is around 0 and the shared environmental effect is much larger. This challenges previous findings in the West. (3) Using a within-twin fixed effect model, we find suggestive evidence on the effect on economic preferences and outcomes, including education performance, income, risk attitudes and subjective well-being. These three studies use the similar behavioral science methodology to study different levels of decision making, and all have important implications for issues of sustainable development.

[3]First author, with Lu Liu

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## Acknowledgements

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## Dedication

To Jiang Wen, for *Let the Bullets Fly*.

To Kong Sheng, for *Minning Town* and *Like a Flowing River*.

To Liu Cixin, for *The Threebody Trilogy* and *Wandering Earth*.

To Cai Haoyu, for *Genshin Impact*.

And to Ni Ni and Zhang Zhen, for *Chen Xi Yuan*.

# Chapter 1: Economic Vulnerability Predicts Social Distancing, and Partisanship Predicts Mask Wearing: Predictors of Compliance with COVID-19 Policies in the US

Non-Pharmaceutical Interventions (NPIs) were the major measures taken against COVID-19 in 2020. From March to November, we observed large regional differences in the level of compliance with the two most important NPIs, social distancing and mask wearing, across the country. With a behavioral model incorporating extrinsic incentives (money returns that mitigate urgent economic scarcity) and intrinsic motivations (expressing partisanship), we hypothesize that (a) economic vulnerability is the key predictor of failure of social distancing, but (b) given the low cost of mask wearing, Republican Partisanship and Conservatism plays the leading role in predicting mask wearing. We test these hypotheses at the county and state levels. Using Standardized Seemingly Unrelated Regressions and coefficient tests, we show that economic vulnerability largely predicts whether or not people work from home, and partisanship largely predicts mask wearing. We further document that Conservatism and Trump support had a larger effect on COVID response after August, when the election was approaching.

## 1.1 Introduction

In the absence of vaccines, contact tracing and forceful quarantine, the most important non-pharmaceutical interventions against COVID-19 have been social distancing (cutting off transmission routes) and mask wearing (both for source control and protection of susceptible hosts). Thus compliance with these two measures is fundamental to preventing the spread of COVID-19. Numerous studies have documented that social distancing and mask wearing causally impact COVID-19 outcomes (Social Distancing, Courtemanche et al. 2020; Hsiang et al. 2020; Lewnard and Lo 2020; Pachetti et al. 2020; Wilder-Smith and Freedman 2020, etc.); Masks, Cheng et al. 2020b; Eikenberry et al. 2020; Howard et al. 2021; Lyu and Wehby 2020,etc). Across the US, we have observed wide heterogeneity in adoption/compliance (a demonstration of the timelines of statewide Shelter-in-place/Stay-at-home order and mask mandates up to Oct 1, 2020 is available below), and people have argued that this may be associated with the regional differences of COVID-19 spread across the country (a demonstration and a contrast to other countries is also shown in the graph).

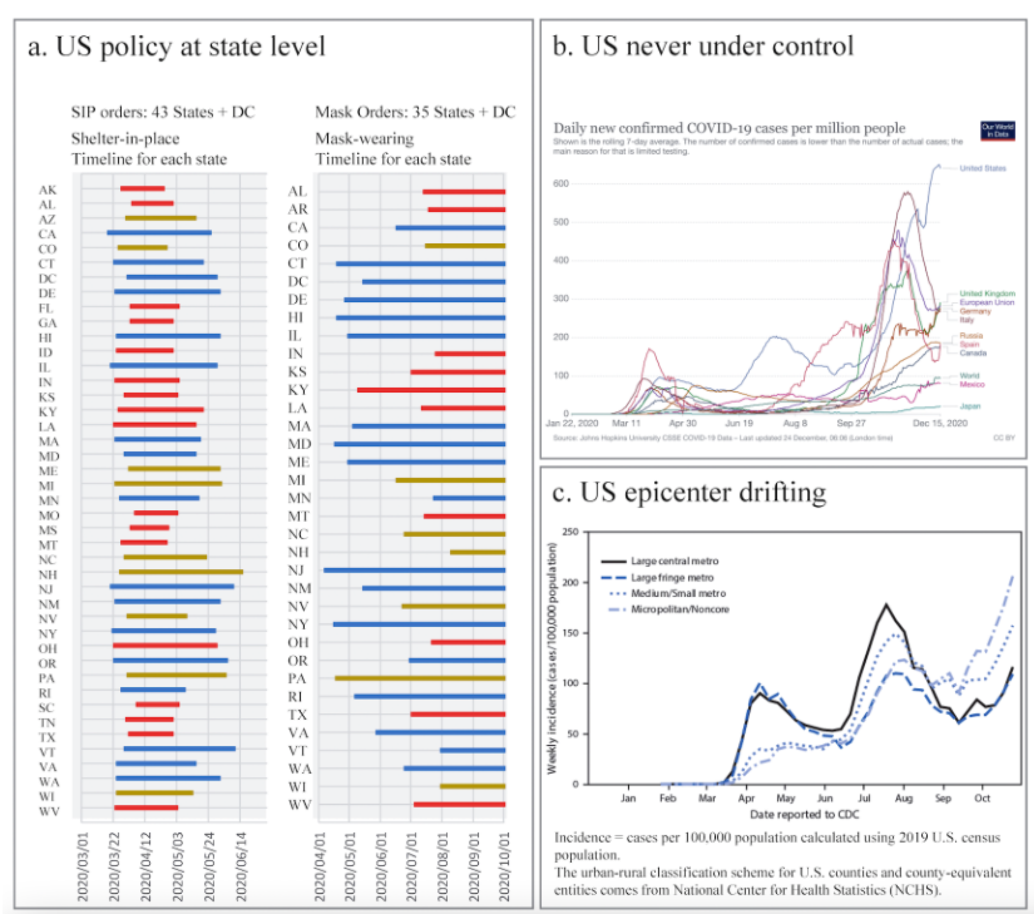



Figure 1.1: Basic Dynamics of the COVID-19 Spread in the United States in 2020

So what explains these variations in compliance? Other than the pandemic severity (which is obvious), there is a large literature about predictors of the determinants of such differences. The most well-known branch focuses on partisanship and ideology (Clinton et al. 2021; Grossman et al.

2020; Kubinec et al. 2020; Painter and Qiu 2020, etc.), suggesting that Republican partisanship or support of conservatism strongly predicts noncompliance with social distancing and mask wearing. Other similar dimensions include institutions, information exposure (Pennycook et al. 2020; Zhao et al. 2020, etc.), culture (Lu et al. 2021; Salvador et al. 2020; Webster et al. 2021, etc.), gender and ethnicity (Hearne and Niño 2021; Pedersen and Favero 2020), religion (Wildman et al. 2020). However, psychological and political reasons are not the whole story. These studies are not able to answer (1) whether partisanship is the *strongest* predictor of social distancing, or there still exist more important ones; and (2) whether there exist systematically different dynamics comparing social distancing and masks. Some studies try to dig one step further: people find that economic indicators that depict the vulnerability of an individual or a region to the economic shocks brought from the pandemic are also incentivizing people's NPIs. Current literature usually focuses on one aspect of this dimension, including income and other economic constraints (Weill et al. 2020), internet access (Chiou and Tucker 2020), work-from-home feasibility (Dingel and Neiman 2020; Mongey et al. 2020) and social safety nets (Warner and Zhang 2021). We build on these factors, tie them together and enrich them into a more comprehensive dimension of the issue. This is called economic vulnerability.

In our study, we establish a behavioral decision-making framework at the individual level and aggregating it into county-level statistical tests based upon the foundations of psychological motivations and economic vulnerability. We use a theoretical framework resembling the framework of the economics literature (Bénabou and Tirole 2006) to give the predictions of the important questions mentioned above and test them empirically. We discuss how economic incentives and psychological motivations differ across behavior and time, and show the mechanisms of the heterogeneity theoretically and empirically.

Economically, a major deterrent for shelter-in-place is that most people have to work away from home (Dingel and Neiman 2020). The extrinsic incentive is to make money – and during a pandemic, people usually work away from home when they really need to do so. The economic incentives are impacted by financial status (Jay et al. 2020; Weill et al. 2020), access to internet

(Chiou and Tucker 2020), and other factors that impact their ability to obtain life resources without working or to work from home. Most non-essential[1] workers are unable to telecommute (Dingel and Neiman 2020; Mongey et al. 2020). Therefore, if the government were to keep shutting down non-essential sectors, these people, especially those who have low insurance and savings level (sometimes referred to as being hand-to-mouth (Kaplan et al. 2014), would face severe financial difficulties without sufficient social safety nets even if they do not belong to low-income cohorts. Thus, as shelter-in-place orders are introduced, urgent economic needs surge and this makes it difficult for the local governments to maintain the compliance of social distancing policies. Unlike social distancing, mask wearing is less affected by economic incentives. For most families, regular masks are affordable, and self-made masks are also an available option (Cumbo and Scardina 2021). Thus, the economic incentives to refuse a mask are low.

For psychological motivations, we suggest that the major motivation is political. Republicans opted to go out to work or refuse a mask regardless of the pandemic severity to express their partisanship, conservative ideology and support for Trump. Researchers have found that Republicans and Democrats may have different reputation and value concerns on social distancing (Allcott et al. 2020; Gollwitzer et al. 2020; Grossman et al. 2020; Painter and Qiu 2020). Firm Republicans may believe that working—and not social distancing—enhances their reputation in a conservative community (Coppins 2020; Rothgerber et al. 2020). This may be attributed to the "information cocoon" effect (Zuiderveen Borgesius et al. 2016). These people get information mostly from conservative media, which repeatedly claimed that COVID-19 was similar to the "flu" and that mask wearing was not necessary (Bail et al. 2018; Cinelli et al. 2020). Numerous studies have shown the highly negative impact of Republican partisanship and American Conservatism in the risk perception of COVID-19 (Allcott et al. 2020; Barrios and Hochberg 2020; Painter and Qiu 2020; Wise et al. 2020), weakening the incentive for social distancing and increasing virus spread (Gollwitzer et al. 2020; Kubinec et al. 2020). These support the idea that partisanship is the dominant effect; and for other correlates, such as culture and religion, we would either treat them as

[1] During the pandemic, essential workers may still work away from home and continue to earn money. However, they only compose a small proportion of population.

a part of psychological motivations (when county-level data is available), or put them in state-level fixed effects.

Consequently, people with a high vulnerability to economic shocks from COVID-19 are more susceptible to pressure to not socially distance. Magnifying this to the regional level, we establish a family of factors that is hypothesized to predict social distancing failure, which we call Economic Vulnerability (EV). Higher economic vulnerability comes from many sources. In the United States, red states in the South are the most economically vulnerable in multiple dimensions (See SM Fig. S4). Southern red states have higher poverty rates (DeNavas-Walt and Proctor 2014; Laird et al. 2018), less coverage of insurances (Berchick et al. 2019), less protection for unemployment[2], and lower level of human capital (DeVol et al. 2018). They are considered high in economic vulnerability compared with the country average, which is already more vulnerable than other developed countries (See SM Fig. S5). Consistent with this, many Southern states had a high level of unemployment filings during the first two months of the COVID-19 outbreak (Amburgey, Birinci, et al. 2020). Southern conservatives also save less than residents of other states and other high-income countries [3]. Moreover, although the United States ranks among the countries with the highest work-from-home potential, most red states do not share this privilege as they have more people working in traditional sectors such as manufacturing and agriculture. All of these features strengthen the economic pressure that pulls people to work away from home during the pandemic. The theoretical discussion and the empirical facts indicate that at least for some places, economic vulnerability might be high enough to be the major determinant of social distancing. On the contrary, such effects would be minor for mask wearing, as we discussed above. Accordingly, we have two hypotheses:

*H1: Compliance with social distancing recommendations and staying home is negatively associated with both economic vulnerability and Republican Partisanship, but the former should have a stronger effect at least when the region-level economic vulnerability is higher.*

*H2: Mask wearing is strongly negatively associated with Republican partisanship and*

[2]https://howmuch.net/articles/unemployment-insurance-benefits-by-state
[3]https://en.wikipedia.org/wiki/List_of_countries_by_gross_national_savings

*American Conservatism, but much less with economic vulnerability.*

This paper summarizes the importance of predictors of social distancing and mask wearing by formally theorizing and testing these hypotheses. These findings are helpful for us to understand the dynamic processes of the formidable COVID-19 spread in the United States. With the incorporation of economic vulnerability, it adds significant evidence on the predictors of COVID-19 response at the regional level. Also, as a vivid real-world test of the famous theory of incentives and motivations, it would deepen our understanding of the complexity in economic incentives and psychological motivations in human decision making. Finally, this perspective of "interdisciplinary horse-racing" has important methodological implications for policy makers, as exploring "which is the dominant force" definitely impacts the effectiveness of real-world intervention on many issues.

## 1.2 Results

### 1.2.1 County-level Analysis

The empirical analysis is a quantification of county-level economic vulnerability and partisanship effects on social distancing and the use of masks.

Our main indicator for social distancing includes four measures from Google Mobility Trends (Aktay et al. 2020) about where people spend their time (home, workplaces, restaurants and grocery stores), from April to November 2020. Since the economic incentives are mainly associated with working, we would expect that the time spent in workplaces should be most impacted by economic vulnerability, and the time spent in restaurants and grocery stores (less essential needs) should be more impacted by psychological motivations. Finally, time spent at home should be mainly determined by going out to work. We choose two sets of masks wearing data: the New York Times-Dynata Survey (Katz et al. 2020) that covers >2,000 counties and 250,000 respondents from July 2-July 17, and Carnegie Mellon University's COVIDCast dataset (Koehlmoos et al. 2020) that covers fewer counties (about 600) from September to November.

In the main results, we separate the timeline into two periods: First, from April to July, during which many parts of the country were under a shelter-in-place order, or at least some restrictive orders enforcing social distancing. Secondly, from August to November, during which most places reopened (but certain places returned to stricter measures) and the only remaining order for many states were mask mandates. We argue that when stay-at-home orders were (fully or partially) in effect, the incentive structures of going out might differ. For instance, the EV might be lower in the second period because the economy was reopened and booming again after the historic decline in April-June. Also, the election campaigns began in August, leading to a higher level of politicization of COVID-19, and many Trump-supporters were protesting against masks and social distancing to show their loyalty.

The following two figures show the determinants of mobility. We use a standardized regression setup, allowing us to compare the relative contributions of the variables of interest to our dependent variable. We controlled for total cases and weekly increase of cases (per capita) till the time of interest, population density, age and gender structures, temperature and other key variables that may impact mobility but not belong to either of our main category.

First, we examined how economic vulnerability and ideology predict social distancing. Although coefficients may differ across time, the basic take-home message is clear. First, during a pandemic, the most indoor time that people spend away from home is in workplaces, and other needs, such as dining in and shopping, are generally minimized and have a lower correlation with staying home [4] . As the county-level correlation between working and staying home is around -0.85, the two have similar predictive power. It is clear that both conservatism (measured by Trump vote shares, religiosity, etc.) and economic vulnerability (lower education, less income, low work-from-home ratio, etc.) are robust predictors for working outside more and therefore, staying home less. The time spent at restaurants and grocery stores are less predicted by economic vulnerability, and more by Republican partisanship. Detailed discussions are in the Appendix.

These two figures (1.2 and 1.3) are regression coefficient plots for economic and ideological variables and social distancing. The left-hand side is a certain response of COVID-19

[4] As mentioned before, at the county level, the Pearson correlation coefficient between time spent at home and workplaces is -0.84 (95%CI: -0.85 to -0.83), while the correlations between time spent at home and other constructs are much lower. And the work-from-home ratio is <40% for almost all states in the US.

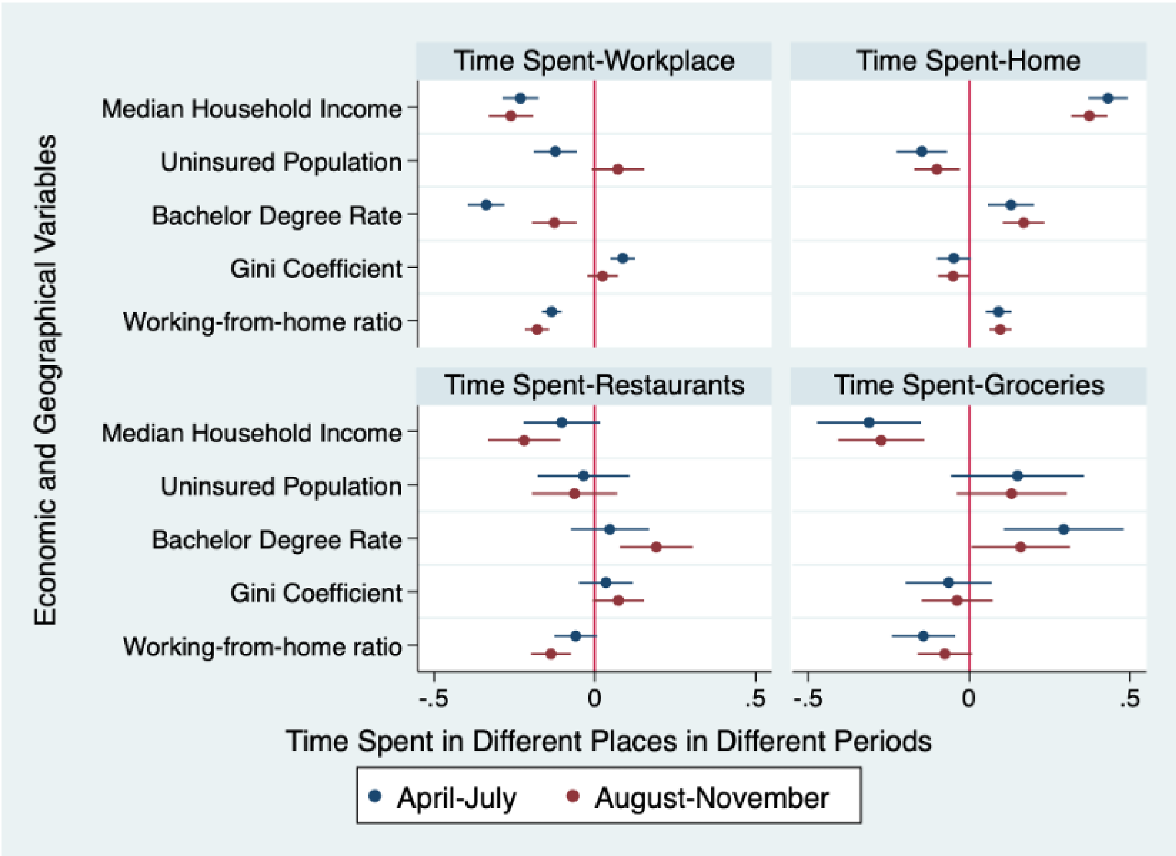



Figure 1.2: Regression Coefficient Plots for Economic Variables and Social Distancing

(time spent in different places). The right-hand side includes controls of lagged cases per capita, recent speed of infection, state*culture [5] interaction terms, and ideological variables. Models are conducted with Ordinary Least Squares (OLS). The round point is the point estimate value, while the lines are 95% CI. The equations are in the Methods part and detailed regression statistics are in the Appendix.

Next, we examine how economic vulnerability and partisanship predict mask wearing. For mask wearing, results are slightly different in the second peak (July) and the third peak (October-November). In July and Fall (Sep-Nov), the best predictor of mask coverage is Trump support, but the coefficient for Fall is significantly more negative. In July, the partial correlation coefficient is -0.21 (95%CI -0.30 to -0.17) being a major but not dominant predictor. However, in

[5] The culture variable is extracted from *American Nations* by Colin Woodard (2011).

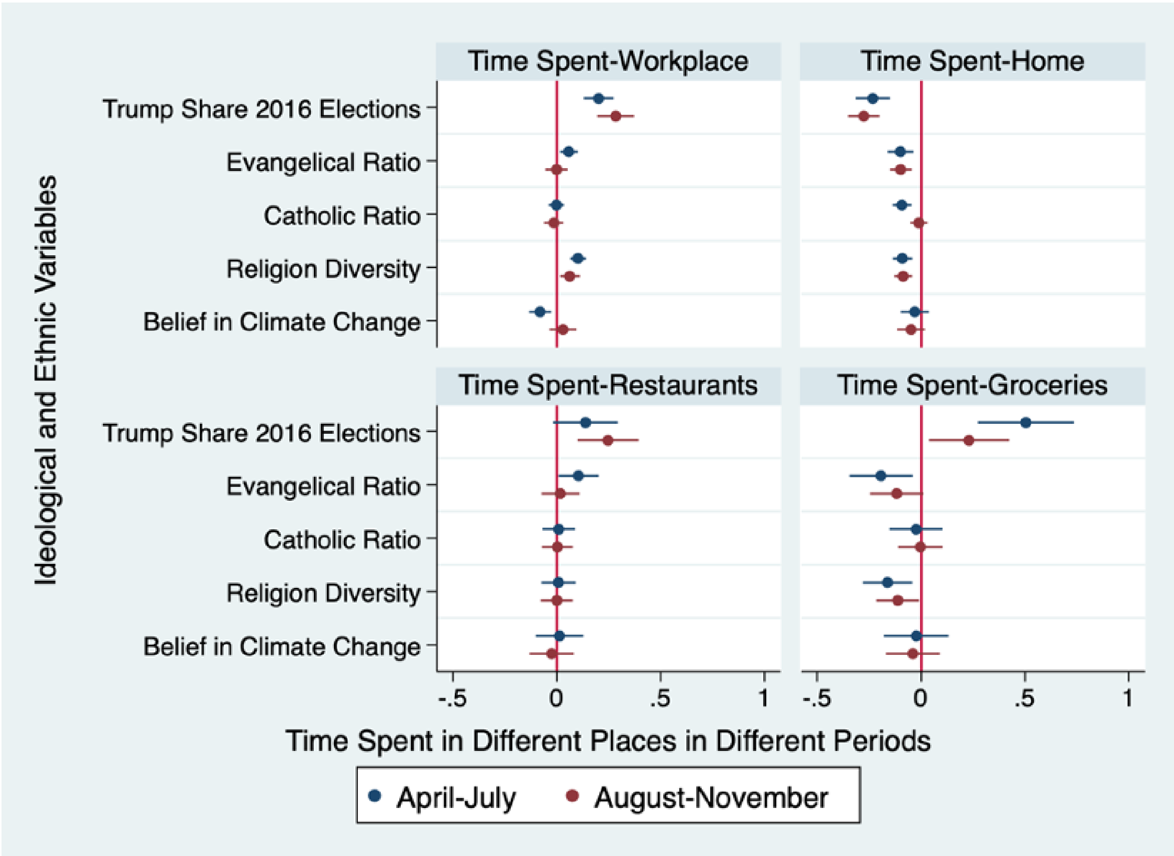



Figure 1.3: Regression Coefficient Plots For Ideological Variables on Social Distancing

October and November, other variables become statistically insignificant or only marginally significant, and the Trump share explains about 40% (partial correlation 0.63, 95%CI 0.50 to 0.75) of the variance in our baseline regressions. This is coherent with our findings on the state-level correlations of Trump support and confirmed cases in the third peak of the outbreak starting in Fall (See Appendix).

This is a regression coefficient plot for economic and ideological variables and mask coverage The left-hand side is a certain response of COVID-19 (mask-wearing). The right-hand side includes lagged cases per capita, recent speed of infection, state*culture interaction terms, and ideological variables. Models are conducted with Ordinary Least Squares (OLS). The round point is the point estimate value, while the lines are 95% CI.

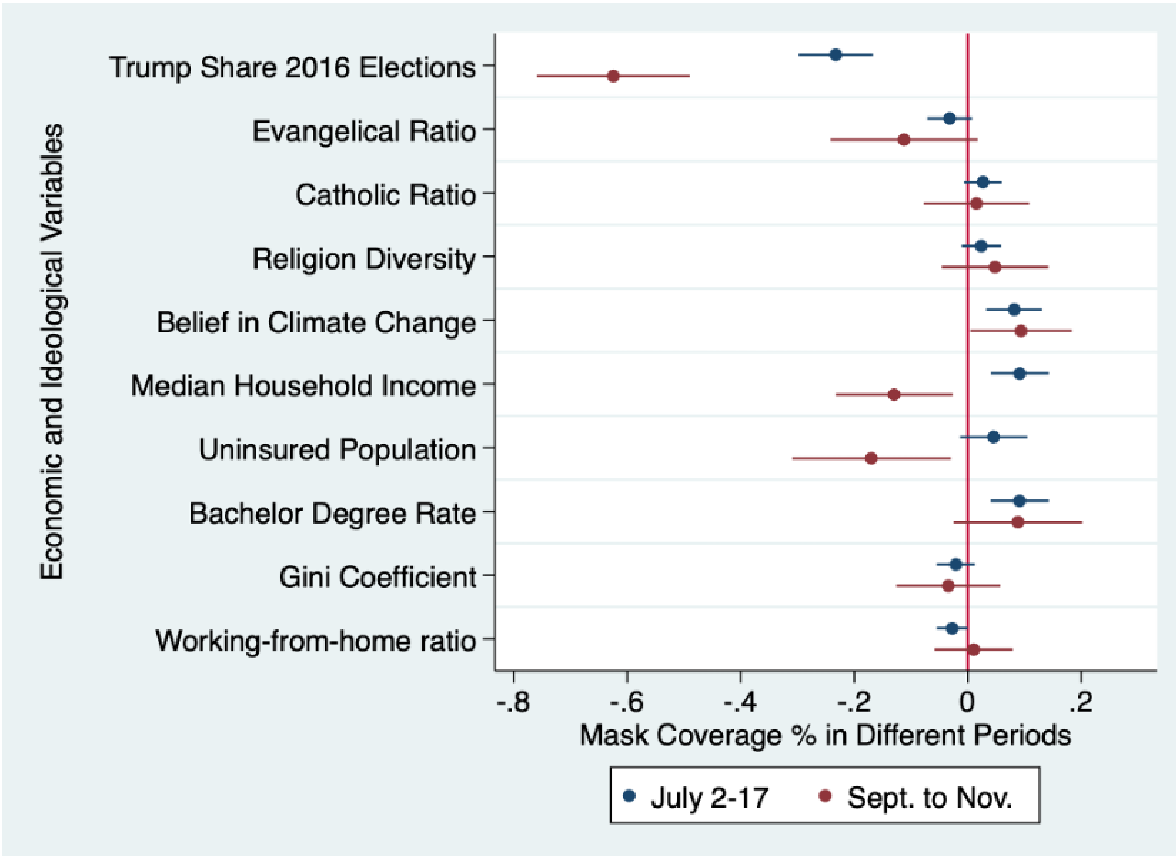



Figure 1.4: Regression Coefficient Plot for Economic and Ideological Variables on Mask Coverage

### 1.2.2 Heterogeneity Analysis for Social Distancing and Masks

In this part, we report formal statistical tests and dynamics of how the marginal effect of economic vulnerability and conservative ideology correlates with social distancing and mask coverage. Our hypothesis and theoretical model (see Methods) will formally discuss three dimensions of heterogeneity:

(1) If we look at regressions explaining working away from home and wearing masks, we should find evidence that within a regression, working away from home is explained better by EV measures than partisanship, while mask-wearing is explained better by partisanship.

(2) If we compare regressions explaining working away from home and wearing masks, we should find evidence that EV measures should have larger coefficients in the regressions of working away from home than those of wearing masks, and partisanship measures should have smaller

coefficients in the regressions of working away from home than those of wearing masks instead.

(3) As time went by, during which EV forces were (arguably) going down and the politicization of COVID-19 increased, for both social distancing and mask coverage, the effect of Republican orientation should be mostly increasing.

To formally test these assumptions, we examine if within a group of regressions, the regression coefficients are different. Since the two behaviors in one county may share similar unobserved factors, the pairwise correlations between error terms are not independent. Thus, we use a Seemingly Unrelated Regression (Nguyen 2010; Zellner 1962) to estimate these models and thereby test our hypotheses. For each of the behaviors (working, stay-at-home and mask wearing), here are three tables for the predictions (1) (2) and (3):

Table 1.1 shows that our first hypothesis is supported by the data, especially in Period 1. Take the stay-at-home time as an example. In the first period, the hypothesis that college degree ratio has a larger coefficient than partisanship is justified at the marginal level ($p \approx 0.10$), while the hypothesis that median earnings has a larger coefficient than partisanship is justified at a highly significant level ($p < 0.001$). In the second period, although the hypothesis that college degree ratio has a smaller coefficient than partisanship is justified at the marginal level ($p \approx 0.08$), the hypothesis that median earnings have a larger coefficient than partisanship is still justified at a significant level ($p < 0.05$). These pieces of evidence show that for social distancing measures, partisanship has a weaker predictive power than economic vulnerability. This indicates that our results add a crucial contribution to the literature because it shows that other than partisanship, EV is likely to be more important determinant for social distancing. For masks, however, EV has a much weaker explanatory power than partisanship in the regressions.

Table 1.2 offers evidence that EV variables have larger explanatory power in Social Distancing regressions while Republican partisanship has larger explanatory power in mask regressions. Note that test coefficients of college degree ratio are generally insignificant. This is likely due to the fast decaying of the effect as time went by (see Figure 1.5)

Table 1.3 shows the evidence that as time reached August (when shelter-in-place orders all ended and election campaigns began), the marginal effect of economic vulnerability goes down and that of Republican partisanship goes up.

Next, Figure 1.5 is a graph that shows the dynamics of the predictive power of some key variables of interest on Social Distancing (working and staying home) on a monthly scale. For masks, due to data availability we only have a two-point comparison, so that at both first-glance observation and rigorous hypothesis testing show good support of our heterogeneity story. As these results converge, we have more confidence that our hypotheses are well supported.


Figure 1.5: Standardized Regression Coefficients of Ideological and Economic Variables across Time

Note: each point is a regression coefficient of the result in certain time periods, in which the dependent variable is the mentioned social distancing variable on a monthly average.

### 1.2.3 Interaction Analysis

Economic vulnerability and partisanship may have interactions. Theoretically speaking, whether this interaction is enhancing people's deviance from SIP[6] is an ambiguous question. On the one hand, according to the theoretical model in the paper, these two motivations may have

[6]For masks, to discuss interaction is unlikely necessary because masks are not strongly linked to economic incentives.

crowd-out effect. When the effect of economic vulnerability is high, people may not need the driving force of partisanship to go working, and vise versa. On the other hand, such effects could also self-enhance when some behavioral assumptions are met. For instance, an Republican agent who suffer from more severe economic vulnerability may use motivated reasoning to persuade herself that COVID-19 is a hoax to avoid feeling dissonance when going out to work. In this case, the perceived cost function would change, making the self-enhancement effect surpass the crowd-out effect. Which is stronger remains an empirical question.

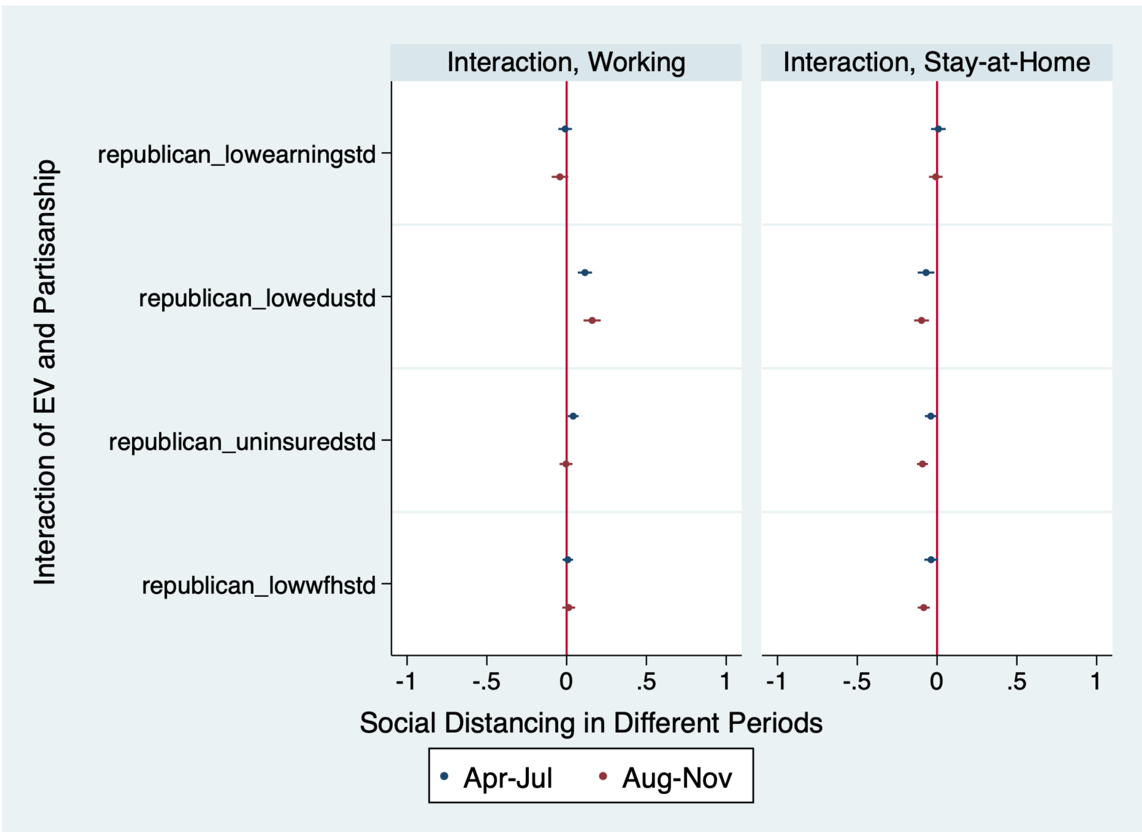



Figure 1.6: Interaction Analysis: Social Distancing

Figure 1.6 is a regression coefficient plot for the interaction of economic and partisanship on social distancing The left-hand side is a certain response of COVID-19 (mask-wearing). The right-hand side is the time of working outside our staying at home. Models are conducted with Ordinary Least Squares (OLS). The round point is the point estimate value, while the lines are 95%

CI.

We can see that some of the coefficients of interaction terms are statistically significant, especially for the interaction of Republican partisanship and education (at a magnitude of about 0.1). This means that being Republican and having a lower education together would especially increase the probability of going out to work during the COVID-19 pandemic. However, such effects are less salient when we look at a lack of insurance or working-from-home chances, and completely fades away when we look at income. On the whole, the second explanation (self-enhancement, rather than crowd-out) plays the major role in determining the interaction effect.

This is an interesting finding, Finally, another reason why we do not detect strong interaction in our regressions is that within a Republican state, the mostly economic vulnerable counties and most Republican counties are distinctive. The revelation of mechanisms would require further investigation.

#### 1.2.4 A Short Review of the Drifting of Epicenters

In our analysis, we show clear time-varying effects in the predictive power of our target variables on COVID-19 response: earlier on, economic vulnerability prevailed and after August, partisanship. State-level analysis also has these implications (for details, see SM). This drives us to look into the whole history of the COVID-19 curve in 2020. The first COVID-19 peak, which mainly took place in Democratic and metropolitan areas from March to May, resembles the first outbreak in other Western countries. The outbreak in the Tri-State area is highly analogous to that in Lombardy, Italy and London, UK. However, the patterns start to be unique in the United States, especially in red states, after mid-May. The second peak mainly took place in the South and is mostly likely explained jointly by economic vulnerability and religiosity, while other dimensions of conservatism seem to have a lower direct influence at the state level. Our model shows a two-step story for these states: in late April, southern states reopened too early without suppressing the effective reproduction number ($R_t$) below 1, or at least, they bounced back over 1 quickly after radical reopening designed for economic recovery[7]. These premature reopening orders took place in Southern states with worse social safety nets (Warner and Zhang 2021), justifying the economic vulnerability story. Consequently, religious activities rebounded immediately with large gatherings and hardly any mask adherence. This made churches crucial in the spreading of COVID-19 (DeFranza et al. 2020). Little changed until mask orders started to cover these states in August and September (See the graph in Introduction). The third wave, starting from Midwest Republican States in October, was more politicized. Our evidence shows that Trump support and Republican partisanship are among the best predictors for not wearing masks and for large numbers of cases in this period. In addition, the epicenters in this peak were likely those states which have a large reliance on agriculture and preference towards limited government interference. The Midwest red states are different than the Southern red states and it was even harder to launch mask and lockdown orders in the Midwest states. Moreover, October was right before the elections, and campaign activities might have enhanced virus spread (Cassan and Sangnier 2020; Pulejo and Querubín 2020). More detailed data visualization and policy demonstration of these three peaks are qualitatively articulated in the supplementary materials. Note that all these findings are correlation-based, and there do exist alternative explanations that we are not able to rule out in this paper.

#### 1.2.5 Limitations and Future Perspectives.

The limitations of this study lie in epidemiological modeling and causal identification. First, in our study, we use a linear dynamic model to show that different factors have highly variable impacts on anti-COVID measures and cases across time. However, the real effects may be nonlinear and may contain more complicated structures. Spatial dependencies are also an crucial point (Cordes and Castro 2020; Franch-Pardo et al. 2020) to address for studying county-level variances. Potential pathways include: (1) effects of common geographical features, such as temperature, wind and humidity; (2) effects of cross-state and cross-county traveling; (3) transportation, such as the distance to international airports, etc. Such effects may cause the standard errors to be

[7] https://rt.live

geographically correlated. In our paper, we use many controls (include state$*$culture, temperature, longitude and latitude) to cope with them. However, to make the analysis more solid, we may need to adjust for such correlations in different ways and justify its robustness.

Second, our findings are mainly partial correlations, which do not necessarily imply causality. To identify and quantify the underlying causal relationships between socioeconomic/ideological variables and COVID response, we need to pin them down in experiments. A natural thought is to reduce the macro-level analysis to the individual level. If we can observe laboratory evidence that these factors causally impact individual attitudes and behaviors, it will give more reliable justification for our whole project.

Third, we have not formally discussed the effects of variables that could not be fully classified as EV/partisanship, such as ethnicity and culture in the analysis. For example, some evidence (see SM) shows that controlling for economic vulnerability and partisanship, counties with larger African American populations tend to have a lower mask coverage rate. This might be associated with a higher proportion of essential workers (for whom it may be difficult to wear masks) or mask stigmatization (African Americans, especially men, may be afraid to be regarded as malicious due to stereotypical thoughts[8]). Also, even within red states, blacker counties had higher infection rates. These findings are speculative evidence that ethnicity also impacts COVID-19 responses, and that African Americans may be subject to asymmetrically high shocks from COVID-19 (Cyrus et al. 2020). Future study may thus look deeper into the ethnic mechanisms.

Finally, we put relatively little emphasis on studying how these responses finally lead to COVID-19 spread. This is mostly because of the huge literature that has already explicitly established this causality. However, people may still want to fully establish the causal contributions of EV and conservatism to the spread of COVID-19 and find counter-factuals; and we suggest that future interdisciplinary research should investigate this.

[8]https://www.statnews.com/2020/06/03/which-deamany-black-men-fear-wearing-mask-more-than-coronavirus/

| | Period 1 (Apr-Jul for SIP) (July for masks) | | Period 2 (Aug-Nov for SIP) (Sep-Nov for masks) | |
|---|---|---|---|---|
| | Bachelor's | Earnings | Bachelor's | Earnings |
| | **Working time: Bachelor's/Earnings vs. Republican** | | | |
| $\chi^2$ | **5.3** | 0.36 | 3.99(Rev) | 0.15 |
| P | 0.0214** | 0.548 | 0.0457** | 0.697 |
| | **Stay-at-home time: Bachelor's/Earnings vs.Republican** | | | |
| $\chi^2$ | 2.62 | **13.4** | 3.13(Rev) | **4.12** |
| P | 0.105 | 0.000*** | 0.077* | 0.042** |
| | **Mask: Bachelor's/Earnings vs. Republican** | | | |
| $\chi^2$ | **8.49** | **15.38** | **30.44** | **102.26** |
| P | 0.000*** | 0.000*** | 0.000*** | 0.000*** |

Table 1.1: Chi-square Tests: Within-regression Comparisons, Different Variables

Notes: This first three rows of this table are the results of chi-square tests of within-regression comparisons of the standardized regression coefficients of partisanship (represented by Trump vote share in 2016), and economic vulnerability (represented by Bachelor's degree ratio and median earnings), with the dependent variable respectively working outside home, staying at home and mask wearing. For instance, the first grid is testing that in the period of Apr-Jul 2020, in a pooled regression (see Methods for the equation), the hypothesis test result of the null hypothesis that the coefficient of Bachelor's degree ratio is larger than that of partisanship. Since the Chi-square value is 5.3, and $p$ <0.05, we can say that we have high confidence that in this period, the predictive power of college degree ratio, a component of EV, is larger than that of partisanship. When there is a "Rev" inside the table (in the third grid the the first row), the value is 3.99 (Rev), suggesting that the predictive power of college degree ration is lower than partisanship, which is actually the reversed result of the main hypothesis (that EV has a larger effect than Republican partisanship/Ideology). In the second and third rows, the logic is the same.

| | Period 1 July | | Period 2 Sep-Nov | |
|---|---|---|---|---|
| | Bachelor's | Earnings | Bachelor's | Earnings |
| | **Working vs. Mask (One IV in two regressions)** | | | |
| $\chi^2$ | 1.44 | **11.60** | 0.09 | **43.43** |
| P | 0.000*** | 0.000*** | 0.6076 | 0.000*** |
| | **Republican Partisanship One IV-coefficient tests in Working/Mask** | | | |
| $\chi^2$ | 1.17 | | **19.12** | |
| P | 0.28 | | 0.000*** | |

| | Period 1 July | | Period 2 Sep-Nov | |
|---|---|---|---|---|
| | **Stay-at-home vs. Mask (One IV in two regressions)** | | | |
| $\chi^2$ | 0.01 | **62.51** | 7.04 | **9.43** |
| P | 0.92 | 0.000*** | 0.008*** | 0.002*** |
| | **Republican Partisanship One IV-coefficient tests in Home/Mask** | | | |
| $\chi^2$ | 0.07 | | **126.8** | |
| P | 0.76 | | 0.000*** | |

Table 1.2: Chi-square Tests: Across-regression Comparisons, Same Variable

Note: This table shows the hypothesis testing results for Hypothesis 2. The values are the coefficient test results of the same IV (College degree ratio, median earnings or Republican ratio) across two regressions at the same period. To make the timing comparable, we choose July for Period 1 and September-November for Period 2. For instance, in the July Regression of median earnings in working outside and mask wearing, the coefficient on working is -0.26 (working is the opposite of Social Distancing) and that on mask wearing is 0.09. The Chi-square test result has value of 11.6, indicating that earnings has a larger effect on working than on mask wearing.

| | Period1 (Apr-Jul) vs Period2 (Aug-Nov) | | |
|---|---|---|---|
| | Republican | Bachelor's | Earnings |
| | | **Working** | |
| $\chi^2$ | **3.41** | **35.33** | 0.89 |
| P | 0.065* | 0.000*** | 0.345 |
| | | **Stay-at-home** | |
| $\chi^2$ | 1.04 | 0.95 | **3.22** |
| P | 0.307 | 0.33 | 0.073* |
| | | **Mask** | |
| $\chi^2$ | **30.68/24.17** | (coefficients insignificant) | |
| P | 0***/0*** | | |

Table 1.3: Cross-time Comparison, Same Variable and Regression

Note: This is a table that compares the standardized regression coefficients of the three representative variables on social distancing and mask wearing behaviors. We use a standard coefficient test from the suest command in Stata. The null hypothesis is that the two coefficients are equal across two periods (for Working and Stay-at-home, Period 1=Apr-Jul, Period 2=Aug-Nov; for mask coverage, Period 1=July 2-17, Period 2=Sep-Nov). The two values of mask wearing is because Period 2 has a much smaller sample size than Period 1 due to data availability. The left value is resulted from directly using SUR on two original regressions, and the right value is resulted from using SUR on the very same sample.

## 1.3 Methods

### 1.3.1 A Explanatory Theory Model

In this model, we analyze the behaviors of non-essential workers who are not able to work from home. We generate our predictions by using a behavioral model derived from the economics literature (Bénabou and Tirole 2006), in which we characterize the behaviors of staying home with different types of motivations. For a typical Republican to determine the time $h$ allocated to work away from home ("outside") during the pandemic, we assume that they are influenced by three factors:

(1) Extrinsic incentives. The job generates an income that can cover their needs. We denote the financial urgency need that can be resolved from one hour's work as $W$, meaning that the more economically vulnerable they are, the higher $W$ is[9]. $W$ is publicly observable. For instance, when the macro-economy faces a downfall, $W$ goes up.

(2) Intrinsic motivations. We assume that a Republican may feel two types of satisfaction during working: First, as a job it satisfies their own values. This value per hour is denoted by $V_r > 0$; Second, it generates reputation gains G within the community, which are jointly determined by the payoff W and the hours $h$, i.e., $G_r = G_r(W, h)$. G should satisfy the following properties: $\partial G_r(W, h)/\partial h > 0$, as Republicans believe that working (instead of staying home) shows their support for Trump and for reopening; $\partial G_r(W, h)/\partial W < 0$ and $\partial^2 G_r(W, h)/\partial W \partial h < 0$, indicating the "crowding out" effect of Bénabou and Tirole: when the extrinsic incentive is higher, observers (community members) are less likely to interpret this behavior as a devotion to Trump, and more likely to see it as self-interested conduct.

(3) Cost. Working has a cost of time lost from other activities and a risk of infection, generating a total cost function $C = C(h)$. As usual, we assume that $C', C'' > 0$. For a typical Democrat, however, motivation structures are different. We have many reasons to believe that they

[9] Usually W is associated with lower but not higher wage. Low-wage workers tend to have less savings and social safety, which means that they tend to face severe economic problems in the pandemic. On the contrary, high-wage workers may already have a lot of savings and assets, so they do not need to take the risk working outside when the pandemic is intensive.

are not working outside for reputation concerns, as they usually had good conformity with stay-at-home orders and did not challenge them from a politicized perspective. An easier setup is just to make the political factors $V_d = G_d = 0$.

*How the Model Led to Our Hypotheses: Comparative Statistics and Theoretical Predictions.* Without losing generality, we assume that for any $h$ and $W, G_r \geq 0$, meaning that any time spent working outside will generate positive reputation for a Republican. We also put important boundary conditions for the reputation function $G_r$. For a Republican, $\partial G_r(0, h_r)/\partial h_r$ is bounded, and for any $h$, as $W \to \infty, G_r \to 0$.

Since we cannot spend negative time working, the optimization problem of a Democratic decision maker is:

$$MaxP(h_d) = Wh_d - C(h_d) \;\; s.t.\; h \geq 0 \tag{1.1}$$

And the optimization problem of a Republican agent will be:

$$maxP(h_r) = (W + V_r)h_r - C(h_r) + G_r(W, h_r) \tag{1.2}$$

Solving the first order condition we have:

$$W + V_r + \partial G_r(W, h)/\partial h_r = C'(h_r) \tag{1.3}$$

Using the implicit function theorem, we have the main condition for comparative statics:

$$\frac{\partial h_r}{\partial W} = \frac{1 + \partial G_r(W, h)/\partial W \partial h_r}{C''(h_r)} \tag{1.4}$$

The predictions of the model for Republicans are determined by the term $\partial G_r(W, h)/\partial W \partial h_r$ (denoted as $G_{Wh_r}$ and its relationship with W. The total time $h_r$ is determined by infection risks and the structures of $G_{Wh_r}$. For working outside, we talk about high-EV ($W$ is large) and low-EV ($W$ is small) cases. When $W$ is large, the reputation motivations of Republicans is small or close to 0. In this case, the partial effect of $W$ on $h$ will be clearly positive.

When W goes to infinity, $\partial h_r / \partial W$ will converge to $1/C''(h_r)$ for both partisans. This is the cases when W has the largest partial effect on social distancing. When $W$ is small, however, for Republicans, $G_{Wh}$ is large such that the partial effect of wage on social distancing is smaller, or even negative. And for Democrats, since $V_d = G_d = 0$, there time spent on working away from home will be very low. When $W \leq C'$, $\partial h_d / \partial W = 0$, indicating that in this case, EV may have no positive partial effect on working outside. When $W \leq C'$, $\partial h_d / \partial W = 1/(C''(h_d)$, indicating that from here on, EV starts to have positive effects on working outside, but it is still below the maximum effect when W goes to infinity.

Our hypothesis takes a perspective from changing W in this model. It leads to the partial effect of EV on social distancing larger when EV is high (in the shelter-in-place period), smaller when EV is low (after July, as the economy reopened), and no effect when EV is 0 (mask wearing). When aggregated to the county level, it generates our final hypothesis: economic vulnerability will have a larger partial effect on social distancing when county-level EV is higher.

A numerical example, which shows an easier understanding of this model, is available in the appendix.

### 1.3.2 Empirical Strategy

Our main hypotheses have the following testable predictions as discussed in the result part. The basic setup of our paper is linear. There are three major branches of hypotheses about the coefficients, and they are tested respectively. First, we want to test the relative effect size of economic vulnerability (EV) and Republican Partisanship within the two measures, social distancing and mask wearing. Then, we want to compare the relative effect size of EV and partisanship across the two measures. Finally, we want to look at how the effect size varies across time. Thus, we can start from the basic regressions as follows:

$$SD_{it} = \beta_{1t} EV_{it} + \beta_{2t} Rep_{it} + \beta_{nt} X_{it} + FE + \epsilon_{it} \tag{1.5}$$

$$Mask_{it} = \beta'_{1t} EV_{it} + \beta'_{2t} Rep_{it} + \beta'_{nt} X_{it} + FE + \epsilon'_{it} \tag{1.6}$$

in which $EV_i$ are the variables related to economic vulnerability, $Rep_i$ are the variables about partisanship and other ideological elements, $X_i$ are the control variables at the county level (such as the accumulated and recent increase of the cases), $FE$ are state-culture fixed effects, and $\epsilon_i$ are error terms. Finally, $t$ is the time period of interest. In the main body of the paper, we focus on two periods: April to July, and August to November.

To test against the first branch of hypotheses, we do chi-square tests for coefficients. However, since $EV_i$ and $Rep_i$ are vectors that has multiple dimensions, we need to refine our testing. Preliminary analyses suggest that for $EV_i$ college degree ratio and median earnings have the highest predictive power, while for $Rep_i$, Republican voter ratio has the highest predict power. Thus, in the body of the paper, we set the coefficients of college degree ratio as $\beta_{11t}$, median earnings as $\beta_{12t}$ and Republican partisanship $\beta_{2t}$. Note that it is expected that $\beta_{11t}$, and $\beta_{12t}$ are positive and $\beta_{2t}$ is negative.

In this way, we need to use the Seemingly Unrelated Regressions (SUR) model to do the testing. on these two measures. Most $\beta'_1$s are the same across the regressions, and we want to test whether the variables of interest have different coefficients that match our hypothesis. The Seemingly Unrelated Regression (SUR) method is used to do coefficient comparisons across regressions that may have correlations in error terms, and it is a good fit for our paper. After running two regressions together with an SUR, we do the chi-square coefficient tests on our three hypotheses respectively:

### 1.3.3 Data

Our research complies with all relevant ethical regulations. Since all data are publicly available from the Internet, these are categorized as exempt according to the UCLA Institutional Review Board. We are unaware of whether participants were compensated. Given the aggregated nature of these data, the sex, age and exact number of participants are unknown. No statistical methods were used to predetermine sample size (in terms of the number of included US counties), but we are covering most counties (3,088 counties) in our sample. Such a sample size allows us to detect and justify small-scale correlations between variables, and to compare the relative strengths of these relationships.

In our county-level regressions, we normalized all our variables by subtracting the mean and then dividing by the standard deviation, so that we can compare the relative predictive powers of different variables of interest.

**Dependent variables**

Our dependent variables fall into three categories: cases and deaths (per capita), social distancing and mask wearing. Here is a brief description in Table 1.4.

For the NYT Mask Wearing data, the aggregation is manual (weighted average by population); for others, the state-level data is directly available on the source websites.

**Independent Variables**

Economic vulnerability indicators capture the state in which local residents might face a cash shortage during the COVID outbreak so that they would oppose lockdown or stay-at-home orders. The state government facing such economic pressure might have to reopen prematurely to revive the economy while the basic reproduction number is still larger than 1. Low incomes and the lack of sufficient social safety nets will both contribute to economic precariousness. We have measures at the state and the county level from various data sources. Industry structures are also related to social distancing. For industry structures, we mainly follow the study by Dingel and Neiman (2020) to compute the work-from-home rate for different states and counties. We also look at the effect of certain sectors and ruralness as robustness checks. In our main regressions, all variables are mean centered and divided by the standard deviation, so that coefficients are comparable in terms of magnitude of influence. At the county level, we are measuring the following variables: poverty rate below federal poverty line (in percentage point), median household income

| Variable | Level | Data Description | Source |
|---|---|---|---|
| *Cases and Deaths* | County and State (see SM) | Daily confirmed cases and deaths of COVID-19 at the county and state level from Feb.15, 2020 to Nov. 30, 2020. | CDC of the United States |
| *Population* | County and State (SM) | Population of the regions to be studied in 2019; used to compute per capita cases and deaths. | CDC of the United States |
| *Social Distancing I* | County and State (SM) | A dataset that shows how visits to places, such as workplaces and homes, are changing in each geographic region. Time Span: Mar-Nov 2020. | Google Mobility Trends |
| *Social Distancing II* | County and State (SM) | A dataset that shows a 7-day trailing average of a fraction of people spending 3-6 hours and >6 hours between 8am-6pm, in one location away from their home. Time Span: Oct-Nov 2020. | Safegraph, Downloaded from COVIDCast |
| *Mask Wearing I* | County and State (SM) | A dataset with 250,000 survey responses on mask use between July 2 and July 14. Response is measured in a 5-item Likert scale, and then aggregated to the county level to compute the total frequency of mask wearing. | New York Times and Dynata |
| *Mask Wearing II* | County and State (SM) | Percentage of people who report wearing a mask most or all of the time while in public, based on surveys of Facebook users. Time Span: Oct-Nov 2020. | COVIDCast (Survey conducted on Facebook) |

Table 1.4: Data Sources of Key Dependent Variables

(in 2010 dollars), proportion of uninsured population (in percentage point), proportion of population with at least a bachelor's degree (in percentage point), degree of income inequality (Gini coefficient), ruralness (the level of being rural, in an index), proportion of agriculture (farming, fishing and forestry) as a part of the economy (%GDP), proportion of population able to work from home (non-adjusted and adjusted; derived from the employment population and wage from NAICS two-digit sectors), Trump share in the 2016 Elections (in percentage point), proportion of people identifying themselves as Evangelical and Catholic (in percentage point), religion diversity (computed from the population of different religious divisions, measured in entropy scores, and details can be seen in a working paper (Ding et al. 2021), proportion of people believing in climate change (percentage point, Howe et al. 2015), proportion of ethnic groups (in percentage point), and cultural zone affiliation (Woodard 2011)). Information of state-level analysis, detailed notes for the sources of the data and their summary statistics can be found in the Appendix.

# Chapter 2: The Political Economy of Responses to COVID-19 in the U.S.A.

Social distancing via shelter-in-place (SIP) strategies, and wearing masks, have emerged as the most effective non-pharmaceutical ways of combatting COVID-19. In the United States, choices about these policies are made by individual states. We develop a game-theoretic model and then test it econometrically, showing that the policy choices made by one state are strongly influenced by the choices made by others. Under certain conditions, if enough states engage in social distancing or mask wearing, they will tip others that have not yet done so to follow suit and thus shift the Nash equilibrium. If interactions are strongest amongst states of similar political orientations there can be equilibria where states with different political leanings adopt different strategies. In this case a group of states of one political orientation may by changing their choices tip others of the same orientation, but not those whose orientations differ. We test these ideas empirically using probit and logit regressions and find strong confirmation that inter-state social reinforcement is important and that equilibria can be tipped. Policy choices are influenced mainly by the choices of other states, especially those of similar political orientation, and to a much lesser degree by the number of new COVID-19 cases. The choice of mask-wearing policy shows more sensitivity to the actions of other states than the choice of SIP policies, and republican states are much less likely to introduce mask-wearing policies. The choices of both types of policies are influenced more by political than public health considerations.

## 2.1 Introduction

The U.S. drew policy researchers' attention during the global COVID-19 Pandemic: to implement non-pharmaceutical interventions (NPIs) or not was all determined by the state government, while for most countries, these policies were implemented at the federal or equivalent level (Holtz et al. 2020; Schuchat et al. 2020). Non-pharmaceutical interventions (NPIs), proven to be key to controlling the COVID-19 pandemic in the absence of vaccination, include testing and contact-tracing (Cheng et al. 2020a), quarantining (Dandekar and Barbastathis 2020; Wilder-Smith and Freedman 2020), shelter-in-place (SIP) or stay-at-home orders (Courtemanche et al. 2020; Lewnard and Lo 2020; Pachetti et al. 2020), and requiring the wearing of masks in public (Eikenberry et al. 2020; Howard et al. 2021; Lyu and Wehby 2020). This state-level policy decision in the U.S. leads to large state-wise differences in policy response, especially on SIP orders and mask mandates.

There are many intrastate factors that contribute to the state-level policy response, and literature has provided abundant evidence, such as the pandemic severity, partisanship (Gollwitzer et al. 2020; Grossman et al. 2020; Painter and Qiu 2020; Van Bavel et al. 2020) and political polarization, economic vulnerability (Chiou and Tucker 2020; Mongey et al. 2020 and the first chapter) and culture (Gelfand et al. 2021; Germani et al. 2020). However, states are not independent entities: they are nested by a variety of connections, and potential interactions may also vacillate the possibility of a state's policy response with respect to others' choices. This is defined as policy spillover or social reinforcement. Once it happens, a state choosing a policy (for example SIP or mask mandate) will promote the probability that other states to follow suit. Such effect was first documented at the country level (Sebhatu et al. 2020) with the OECD dataset, showing that policies in a certain country may have "diffusion effects" outside its boundaries. In our study, however, we show that such patterns happen within the United States.

This study is motivated by the following observations that have depicted the US states' policy responses to COVID-19 within the year 2020. First, from the perspective of individual states and regions, there exist strategic complementarity effects in policy choices. Take the tri-state area of New York, New Jersey and Connecticut as an example, where many residents of all these states commute to and work in New York City (NYC). From the economic concerns, a full lockdown in NY would reduce the incentives for NJ and CT residents to commute, making it easier for NJ and CT governors to do likewise (Mollalo et al. 2020). From the political concerns, the policy choice by one state may make it politically easier for others to follow suit (Sebhatu et al. 2020). There is a strong mutual influence by COVID-19 in those three states. Secondly, from a nationwide perspective, the policy timelines shows that states with the same partisanship tend to move together (Cui et al. 2021)[1], and there are clusters that correlate with partisanship and geographical adjacency. There are obvious time differences as Democratic and Republican states chose to launch policies. These first-glance findings drive us to see the policy implementation of states as interdependent, and we are specifically interested in studying whether this interdependent is a dominant factor in shaping state behaviors.

To do so, we move one step further in modeling a state governor's interdependent policy choice: we take inter-state influence into consideration following the literature of supermodular game, especially multi-player coordination games. These games usually have multiple Nash equilibria, including a greatest (Pareto Optimal) and a least equilibrium. When using this framework to our topic, it means that a state utilizes not only her own policy choice but also others' choices. By assuming that a state will be better off choosing one policy as the number of other states that choose the same policy goes up, the game between states is characterized by social reinforcement, and in particular its payoffs may show what is called uniform strict increasing differences in previous work (Heal and Kunreuther 2010; Kunreuther and Heal 2003) , a strong form of strategic complementarity. This depicts an effect of social reinforcement, or positive externality, across state-level policy choice.

We model this complementarity for policy making by showing the existence of tipping sets and tipping patterns. A tipping set in such a game is a set of players (states) with the following property: if all members of this set have the same choice (to implement the same policy or no policy), then the best response of every other agent will be to follow suit: this is called that the equilibrium is tipped to the greatest equilibrium (i.e. every state takes the NPI) by the tipping set. In this case, states in a tipping set can drive all others to the adoption of NPIs, even in the absence of a federal mandate for such policies. In a more preliminary study (Cui et al. 2020), we showed this

[1] For instance, more than 50% of democratic states clustered around late March in conducting SIP orders.

pattern may theoretically work for the entire country. And in this paper, we introduce partisanship and shows that it may interact with the tipping pattern. We show that under certain, plausible assumptions (see Methods), there exist the following patterns: at the equilibrium where no states have NPIs, a subset of the democratic states can tip the remaining democratic states to the equilibrium where all have NPIs and no republican states do. Similarly, at the equilibrium where all states have NPIs, a subset of the republican states can tip the remainder to the equilibrium where only democratic states have NPIs. If the real process resembles tipping, we can formally justify that the policy interdependence is a crucial factor that shapes state-level policy making on COVID-19.

Empirically, we use a random utility setup to test the theoretical implications. Under the random utility assumption, the policy choices of an individual state can be characterized by a daily-basis longitudinal Probit/Logit model. The probability for a state with an effective SIP or mask-wearing order for any given date is a function of several factors: whether this state is democratic or republican, the proportions of states separately within democratic, republican and swing groups that have already introduced such orders on that day, the severity of COVID-19 which is measured by that day's number of new COVID-19 cases per 100k population in the state, and unobserved determinants of the utility. Estimated results show that when the state's partisanship is fixed, its policy decision mostly rely on the proportion of other same-partisanship states with an effective SIP or mask-wearing order, even compared with other known factors such as the severity of the pandemic and the economic conditions. This confirms the importance of social reinforcement at the state level and therefore justify our theoretical model. We also find evidence on the existence of tipping sets, particularly for mask-wearing orders. The probability of launching a mask order sharply responds to the proportion of same-partisanship states which have already launched one. For SIP orders, however, such effect is much less sharper.

This paper answers four central questions about the ways in which state governors engage in COVID-19 prevention policies. Rather than merely focus on local COVID-19 severity, the governor for one state do pay more attention to other states' policy choices before deciding its own response, even when we control for the average differences across states in any observable or unobserved characteristics. Next, among other states' choices, it is the policy choices of states with the same political ideology that impacts the most on the decision of a state governor. Furthermore, spontaneous policy responding is feasible once a threshold of the number of states already engaged in COVID-19 prevention policies is met: a tipping set can automatically tip the rest of states into an effective NPI order without the intervention of the federal government. Finally, the extent to which tipping differs across policies. Mask policies are better approximated than SIP policies, which is likely explained by the larger level of politicization of masks than SIP.

This paper contributes to the literature in the following senses: (1) It is the among the first studies to use a coordination game framework to analyze the policy behaviors during COVID-19, and thereby highlighting the interdependence of policy choices across states. (2) This study offers two interesting comparisons that discuss about the intensity of interdependence of policy: other states' choices are more important factors than severity, and mask mandates have larger level of interdependence than SIP policies. The findings on these differences indicate the complicated incentive structures of policy making on epidemiology, showing that in real world, political and socioeconomic factors may dominate epidemiological ones in decision making. (3) It is among the first studies to empirically test the theory of policy tipping in a non-laboratory environment, showing that when there is enough response time, entities may converge to some collective action outcomes which highly resemble the theoretically predicted equilibria. Thus, it sheds light on future policy research and pulls them to consider more complicated externality between different entities.

## 2.2 Model and Methods

### 2.2.1 Theoretical Model

There are $I$ agents (states) indexed by $i = 1, 2, ..., I$. Each has a strategy $s_i$ and a strategy space given by two alternatives $\{0, 1\}$ where $s_i = 0$ denotes either no SIP or no mask-wearing policy and $s_i = 1$ indicates that such a policy is in place. We model the choices of SIP or mask-wearing policies separately, and do not consider the interactions between them (except in the empirical appendix, where we show that allowing for this makes little difference to our results).

The vector $S \in R^I$ represents the list of strategies chosen by all agents $S = (s_1, s_2, ...s_I)$ . Each agent's payoff function $U_i(S) : S^I \rightarrow R^1$ depends on the choices of all agents, its own and those of others. We let $0_i$ or $1_i$ denote a zero or a one in the $i-th$ position of $S$ and the vector $S_{-i}$ be the vector of all choices made by states other than $i$. We assume that the $U_i$ all satisfy uniform strict increasing differences, that is using the usual vector ordering on $R^I$, $\exists \epsilon > 0 : \; S'_{-i} > S_{-i} \;\Rightarrow$

$$U_i\left(1_i, S'_{-i}\right) - U_i\left(0_i, S'_{-i}\right) \geq \epsilon + U_i\left(1_i, S_{-i}\right) - U_i\left(0_i, S_{-i}\right) \tag{2.1}$$

In words, consider two configurations of strategy choices by players other than $i$, denoted $S_{-i}$ and $S'_{-i}$. Then if in $S'_{-i}$ at least one state has changed from zero to one relative to $S_{-i}$, which is implied by $S'_{-i} > S_{-i}$, then the payoff to state $i$ to changing from zero to one is strictly and uniformly greater at $S'_{-i}$ than at $S_{-i}$. This means that agent $j$ changing from zero to one raises the payoff to this change for agent $i \neq j$ for any $i$ and $j$. This is implied by the interactions between state strategies discussed above: the adoption of an SIP or mask policy by state $j$ makes such a policy more attractive for state $i$. In the inequality (2.1) the parameter $\epsilon$ is a measure of the degree of social reinforcement: the greater is $\epsilon$, the greater is the degree of social reinforcement or strategic complementarity and as we will see below the smaller is the tipping set. For simplicity we are assuming the $\epsilon$ to be independent of the states involved, though the discussion above of the tri-state area makes it clear that in reality some pairs of states reinforce each other more than other pairs. Think of New York and New Jersey versus New York and Alabama.

Tipping sets are important in this analysis. Intuitively a tipping set is a subset $T$ of players which has the following property. If all the members of $T$ choose strategy 1, then the best response for any other player is strategy 1. If all members of $T$ choose SIP orders, then every other state finds that its best strategy is also to choose an SIP order. Formally, if $S_i = 1 \forall i \in T$, then $\forall i \notin T, \; U_i(1_i, S_{-i}) \geq U_i(0_i, S_{-i})$. A minimal tipping set is a tipping set with the property that no strict subset is also a tipping set.

### 2.2.2 Empirical Methods

In order to implement these ideas empirically we modify the theory developed above to include a random utility element. We assume that the states' preferences are represented by utility functions with a random term:

$$U_i(s_i, S_i) = V_i(s_i, S_i) + \mathbf{E}_i(s_i, S_i) \tag{2.2}$$

where the $\mathbf{E}_i(s_i, S_i)$ are a set of random variables with mean zero whose distributions depend on the strategies chosen by states. Each state has to evaluate the difference between adopting and not adopting a policy, i.e. between $s_i = 0$ or $s_i = 1$. This difference, the payoff to policy adoption, is

$$\Delta U_i\left(S_{-i}\right) = V_i\left(1, S_{-i}\right) - V_i\left(0, S_{-i}\right) + \epsilon_i\left(1, S_{-i}\right) - \epsilon_i\left(0, S_{-i}\right) \tag{2.3}$$

which may be negative even though $V_i\left(1, S_{-i}\right) - V_i\left(0, S_{-i}\right) > 0$. We can rewrite as (2.3) as

$$\Delta U_i\left(S_{-i}\right) = \Delta V_i\left(S_{-i}\right) + \Delta\epsilon_i\left(S_{-i}\right) \tag{2.4}$$

Note that if the $\epsilon_i$ are multivariate normally distributed then the $\Delta\epsilon_i$ are normally distributed and the parameters of the utilities can be estimated by a Probit regression. If they are identically and independently distributed with extreme value distributions then the $\Delta\epsilon_i$ are distributed as a logistic distribution, meaning that the system can be estimated by a logit regression (see Hausman and Wise Hausman and Wise 1978). In the following analysis we use both approaches.

In this section we use data on shelter-in-place orders, mask-wearing orders and COVID-19 cases at the state level to test the ideas discussed above. We know the date at which each state in the U.S. introduced (or rescinded) a mask-wearing order or SIP order (if in fact it did), and we have data on the numbers of COVID-19 cases by state by day. We classify each state as Democratic, Republican, or swing: a state is Democratic (Republican) if it has two Democratic (Republican) senators and at least 48% of the vote was for Clinton (Trump) in 2016, or if it has one Democratic

(Republican) senator and at least 50% of the vote was for Clinton (Trump) in 2016. The remainder are swing states. We have 51 states in total (we treat Washington D.C. as a state), of which 16 are Democratic, 26 Republican and 9 are swing states[2].

We use discrete choice models (probit, logit and linear probabilities) and also conventional linear regression models to test whether the policies of one state can have an impact on the choices of others, and find unambiguous support for this. We also test for tipping, which in the probit-logit context we define as follows. Democratic states that have adopted a policy can remaining democratic states tip (or republican or swing states) to adopt a policy (which could be shelter-in-place or wear masks) if whenever the fraction of democratic states which have adopted the policy exceeds a fraction $x$, then the probability of the other states (remaining democratic etc) adopting the policy is one.[3]

We find substantial support for the theoretical framework set out in the theoretical sections, but do note differences between the factors determining the choices of mask-wearing policies and SIP policies. There is clearer evidence of tipping in the case of mask-wearing: a state's choice of mask-wearing policies responds more sharply to changes in the choices made by other states than the choice of an SIP policy. There are also differences between the responses of democratic and republican states.

This difference between responses on mask-wearing and SIP policies is predictable because SIP has a real economic cost for anyone who cannot work from home. Hence it is opposed by economically vulnerable populations.[4] Mask-wearing, in contrast, has no or little economic cost, but can be seen as a signal of partisanship. Not wearing a mask was adopted as a signal of support for Trump and skepticism about the importance of COVID-19 and the appropriateness of policy

[2]The number of new cases per day for each states is taken from https://covidtracking.com/api/v1/states/daily.json. The dates on when mask-wearing policies are introduced or rescinded come from https://edition.cnn.com/2020/06/19/us/states-face-mask-coronavirus-trnd/index.html Population data comes from https://www.census.gov/data/tables/time-series/demo/popest/2010s-state-total.html We experiment with other definitions of republican, democratic and swing states and find that our results are not sensitive to these choices.

[3]Setting the probability of adoption by Category B equal to 1 makes this a strong definition of tipping: a probability of 0.9 or 0.95 would also be defensible.

[4]Economically vulnerable populations are those who cannot work from home, who have limited savings and whose states have limited social safety nets.

measures aimed at it. This suggests that the factors that influence choices about enacting policies are different in the two cases, with economic factors weighing more heavily in SIP choices and political/symbolic factors more important in mask-related policies. The evidence in the first chapter is a good support for this.

This can explain democratic-republican differences. Republican states are more likely to contain economically vulnerable populations who stand to lose from SIP policies and so will be more reluctant to such policies. And republican states can also be expected to be less receptive to mask-wearing because of its symbolism.

## 2.3 Results

### 2.3.1 Mask-Wearing

Based on the empirical methods mentioned above, we use discrete choice models to estimate the probability of a state without a mask-wearing order, adopting one on day $t$. The underlying hypothesis is that the probability of a state without such a policy adopting a mask-wearing policy depends on the number of other states of its political orientation that have already done so, the numbers of other states of different political orientations that have done so, and the number of COVID-19 cases in the state. The model being estimated[5] is

$$P_{i,t} = \alpha_i N_{D,m,t} + \beta_i N_{R,m,t} + \gamma_i N_{S,m,t} + \delta_i C_{i,t} + K_i + \epsilon_{i,t} \tag{2.5}$$

where $P_{i,t}$ is the probability that state $i$ adopts a mask-wearing order on day $t$, $N_{D,m,t}$ is the fraction of democratic states that have adopted mask-wearing orders by date $t$, $N_{R,m,t}$ is the fraction of republican states that have done likewise by date $t$ and $N_{S,m,t}$ the fraction of swing states that have mask-wearing orders in place. $C_{i,t}$ is the 7-day moving average number [6] of new COVID-19 cases per 100,000 of population in state $i$ at date $t$, $K_i$ is a constant and $\epsilon_{i,t}$ is a NID serially independent

[5] Fixed effects are not allowed for Probit and Logit models.

[6] New cases are 7-day MA (day t-6 to day t), since the moving average should not include anything after time t because policy making should not rely on future cases.

| | *Probit* | | *Logit* | | *LPM* | |
|---|---|---|---|---|---|---|
| | *R* | *D* | *R* | *D* | *R* | *D* |
| $N_{D,m,t}$ | $29.04^{**}$ | $19.73^{***}$ | $18.08^{***}$ | $56.52^{***}$ | $-0.123^{***}$ | $0.946^{***}$ |
| $N_{S,m,t}$ | $13.02^{*}$ | $20.87^{***}$ | $12.45^{**}$ | $49.82^{***}$ | $0.616^{***}$ | 0.274 |
| $N_{R,m,t}$ | $28.53^{***}$ | $31.78^{**}$ | $23.30^{***}$ | $69.49^{***}$ | 0.0554 | $-0.235$ |
| $NC_{i,t}$ | $0.349^{***}$ | 0.0241 | $0.203^{***}$ | 0.042 | 0.00203 | $0.0066^{*}$ |
| $K_i$ | $-55.25^{***}$ | $-18.54^{***}$ | $-31.07^{***}$ | $-25.36^{***}$ | $-0.0135$ | $-0.0789^{**}$ |
| $lnsig2u$ | $6.513^{***}$ | $5.05^{***}$ | $5.838^{***}$ | $6.85^{***}$ | | |
| $N$ | 3978 | 2448 | 3978 | 2448 | 3978 | 2448 |

Table 2.1: Probit, Logit and LPM Regressions for Republican and Democratic States

Note: Dependent variable is the probability of a mask-wearing order. *, ** and *** denote significant at 5%, 1% and 0.1% levels. The LPM regression contained state-level fixed effects.

error process. We can think of (2.5) as an implementation of the random utility equation (2.4), with the RHS a linearization of $\Delta V_i\ (S_{-i})$ and the probability of choosing a mask-wearing policy being given by the utility gain from such a policy.

Our basic approach assumes that the probability of choosing to implement a mask-wearing policy is independent of whether or not there is an SIP policy in place, which is a strong assumption. In the appendix, where we conduct robustness checks, we allow the selection of a mask policy to depend on whether there is an SIP policy in place: the results show that it does not, and that our specification is robust. We run equation (2.5) using Probit, Logit and Linear Probability models, separately for Democratic and Republican states. The results are summarized in Table 2.1.

The coefficients of $N_D$, $N_S$ and $N_R$ in the Probit and Logit regressions are all positively significant, which means that the numbers of other states that have adopted mask-wearing rules has a significant and positive association with the likelihood of a state adopting such rules, whether it is Republican or Democratic. The number of current COVID-19 cases, however, has no significant association, rather surprisingly.

With Logit and Probit regressions, the values of the coefficients have no simple interpretations: the coefficient on an independent variable does not give the partial derivative of the dependent variable with respect to that independent variable. What matters is the sign and the significance of a coefficient, which establish whether the independent variable matter and qualitatively what its effect is.

In a Probit estimation the underlying equation is

$$P_{i,t} = \Phi \left\{ \alpha_i N_{D,m,t} + \beta_i N_{R,m,t} + \gamma_i N_{S,m,t} + \delta_i CC_{i,t} + K_i + \epsilon_{i,t} \right\} \tag{2.6}$$

where $\Phi\{.\}$ is the cumulative normal distribution. The marginal effect of $N_{D,m,t}$,the derivative of $P_{i,t}$ with respect to $N_{D,m,t}$, is $\alpha_i \Phi' \{.\} = \alpha_i \phi \{.\}$ where $\phi$ is the normal density function. Clearly the derivative depends on the values of the other independent variables, and of course depends on the value of $N_{D,m,t}$. In the tables that follow we present the partial derivatives of the dependent variable with respect to selected independent variables. In doing this, we set the variables other than the mask-wearing rate with respect to which we are differentiating equal to either their sample means or to their maximum values, and report the marginal effect (derivative) for all possible mask-wearing rates. Table 2.2 shows the marginal effect of a change in the democratic mask rate $N_{D,m,t}$ as it varies from zero to one and all other variable are at their sample means,[7] according to both probit and logit models.[8] The first column shows $N_{D,m,t}$ the democratic mask rate, the second the probability of a mask-wearing policy being implemented in a democratic state according to the probit model, the third the change in probability (the marginal effect), the fourth and fifth columns the same for a republican state, and the remaining columns repeat this for the logit model.

Table 2.2 shows that according to the probit model, a change in $N_{D,m,t}$ from 0.3125 to 0.3750 increases the probability of a democratic state implementing a mask-wearing order by 0.54. The equivalent number for the logistic model is even larger, 0.78, and occurs when the mask rate changes from 0.1875 to 0.3125. So democratic states have a big impact on democratic states: table 2.2 also shows that they have no impact on republican states. All these comments are conditioned on the values of the other independent variables being equal to their sample means. The probit

[7] When they are at their maximum values, the probability of a democratic state introducing a mask-wearing policy is constant at one.

[8] The table omits mask rate below 0.0625 and above 0.5625 as the probability is constant at zero and one respectively in these ranges.

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{D,m,t}$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ |
| 0.0625 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 0.1250 | ” | ” | ” | ” | ” | ” | ” | ” |
| 0.1875 | ” | ” | ” | ” | ” | ” | ” | ” |
| 0.25 | 0.034 | 0.034 | ” | ” | ” | ” | ” | ” |
| 0.3125 | 0.277 | 0.243 | ” | ” | 0.18 | 0.18 | ” | ” |
| 0.3750 | 0.88 | 0.463 | ” | ” | 1.00 | 0.82 | ” | ” |
| 0.4375 | 0.97 | 0.23 | ” | ” | ” | ” | ” | ” |
| 0.5000 | 1 | 0.03 | ” | ” | ” | ” | ” | ” |
| 0.5625 | ” | ” | ” | ” | ” | ” | ” | ” |

Table 2.2: Marginal Effect of Change in Democratic Mask Rate

Note: other independent variables set equal to sample means.

analysis in Table 2.2 shows that once 43% of democratic states have adopted mask-wearing orders, the probability that any remaining democratic state will follow suit is one. The logit analysis places the tipping point slightly lower, at 38%.

Table 2.3 repeats Table 2.2 but for changes in $N_{R,m,t}$, the republican mask rate with other independent variable set at their maximum values.[9] We see that a change in the republican mask rate has no impact on democratic choices, but a significant impact on the choices of republican states. According to the the probit model a change in $N_{R,m,t}$ from 0.23077 to 0.26923 raises the probability by 0.47, and according to the logistic model an increase from 0.15385 to 0.19231 raises the probability by 0.52. The probit analysis in Table 2.3 shows that once 35% of republican states have adopted mask-wearing orders, then the probability that the remaining state will also adopt such orders is one. The logistic analysis gives a slightly lower tipping point, 27%.

In Figure 2.1 we explore how the probabilities of choosing a mask-wearing policy respond to independent variables more multidimensionally, looking at two-dimensional subspaces of the four-dimensional space of independent variables. We vary the mask-wearing rates for democratic, republican and swing states, holding the rate of new COVID-19 cases constant at its mean value.

[9] When the other variables are at their sample means, the probability of a republican state choosing a mask-wearing policy is always zero.

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{R,m,t}$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ |
| 0.07692 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| 0.15385 | ” | ” | ” | ” | ” | ” | ” | ” |
| 0.19231 | ” | ” | 0.01 | 0.01 | ” | ” | ” | ” |
| 0.23077 | ” | ” | 0.12 | 0.11 | ” | ” | 0.04 | 0.04 |
| 0.26923 | ” | ” | 0.49 | 0.37 | ” | ” | 0.21 | 0.17 |
| 0.30769 | ” | ” | 0.86 | 0.37 | ” | ” | 0.53 | 0.32 |
| 0.34615 | ” | ” | 0.98 | 0.13 | ” | ” | 0.84 | 0.31 |
| 0.38462 | ” | ” | 1.00 | 0.00 | ” | ” | 0.97 | 0.13 |
| 0.42308 | ” | ” | 1.00 | 0.00 | ” | ” | 1.00 | 0.00 |

Table 2.3: Marginal Effect of Change in Republican Mask Rate

Note: other independent variables set equal to maximum values expect for new case rates (95% qt or mean for Probit/Logit respectively.

Figure 2.1 shows on the horizontal axes the percentages of states adopting mask-wearing policies (republican and swing states: in these figures red = republican, blue = democratic), on the vertical axis the probability of a democratic state that has not adopted such a policy doing so, with the percentage of democratic states that already have mask-wearing policies in place increasing from top left to lower right, going from 18% to 31% and ending at 68%. Each of these figures is a two-dimensional slice of the four-dimensional space of independent variables, in the plane defined by the mask adoption rates of swing and republican states. The adoption rate of the democratic states varies from one panel to the next, so taken together they are points in a three-dimensional subspace of the space of independent variables.

For low democratic rates of adoption of mask policies, there is an area of low swing and republican rates where there is zero probability of a democratic state adopting a policy, and one of high swing and republican rates where this probability is one, with a rather sharp transition between them: for higher democratic rates the area of zero probability is almost non-existent and corresponds to zero rates for the other two categories of states. The sharp transitions here from probabilities of zero to one do seem to correspond well to the notion of tipping discussed in the theoretical model.

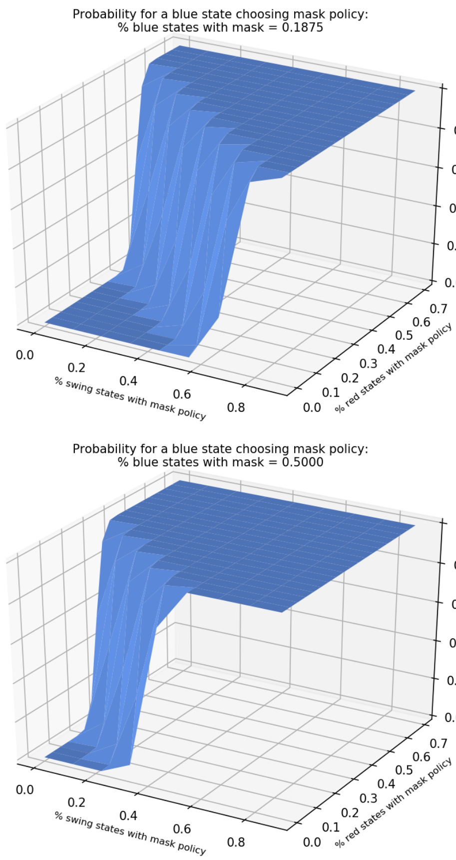



Figure 2.1: Democratic Mask-wearing Responses to Other States' Choices

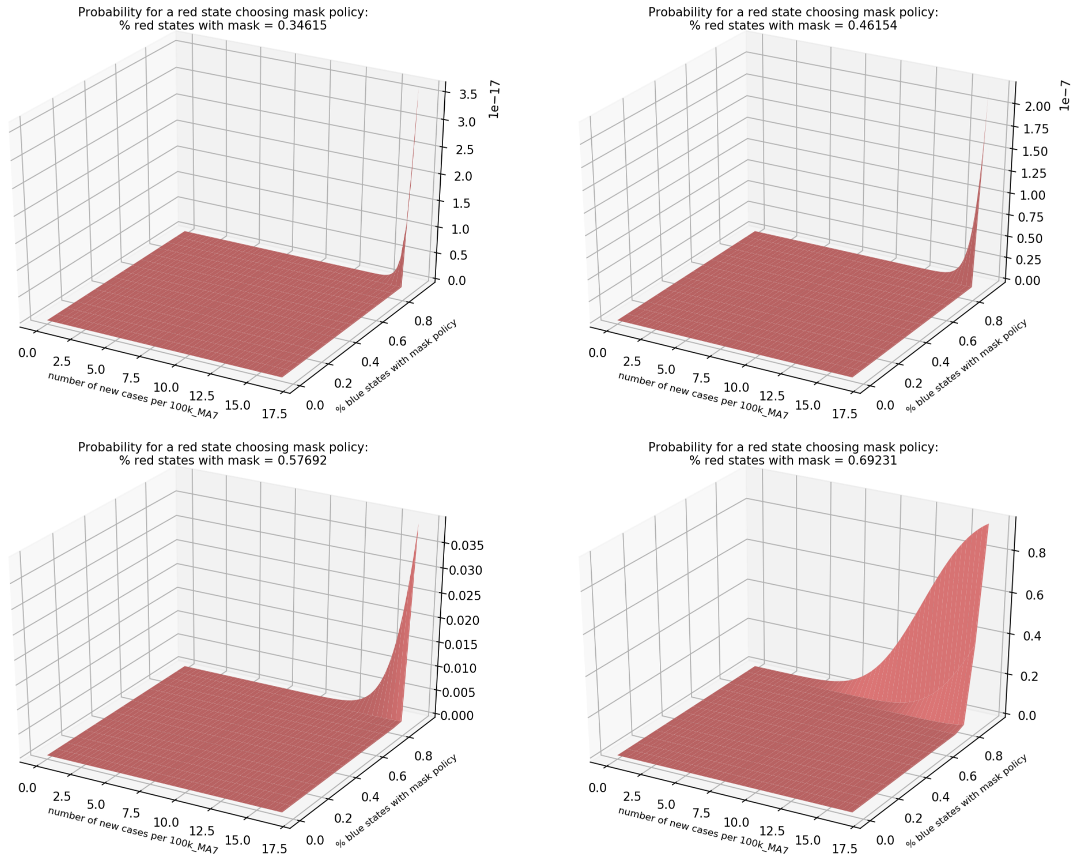



Figure 2.2: Republican Mask-wearing Responses to Other States' Choices

Figure 2.2 shows the same data for republican states, and portrays a very different story. It is almost impossible for other states to induce a republican state to adopt a mask-wearing policy. Only if both other categories are at 100% adoption and nearly 50% of republican states have adopted too, will the probability of a remaining republican state go to one. Again the transition is sharp, the gradient of the response surface high, so that there is again tipping but in much more limited circumstances.

### 2.3.2 Shelter-in-Place Orders

In this subsection we use discrete choice models to estimate the probability of a state without an SIP order, adopting one on day $t$. The estimating equation is (2.7): the dependent

| | Probit | | Logit | | LPM | |
|---|---|---|---|---|---|---|
| | *Rep* | *Dem* | *Rep* | *Dem* | *Rep* | *Dem* |
| $N_{D,SIP,t}$ | 5.739*** | 2.587*** | 10.65*** | 4.289*** | −0.058 | 0.77*** |
| $N_{S,SIP,t}$ | −2.010** | 2.800*** | −3.677** | 5.536*** | 0.208** | 0.315*** |
| $N_{R,SIP,t}$ | 8.393*** | 3.600*** | 15.22*** | 9.0669*** | 0.782*** | −0.623 |
| $NC_{i,t}$ | 0.0378 | 0.0428*** | 0.055 | 0.0817*** | 0.00017 | -0.0004 |
| $K_i$ | −9.273*** | −2.892*** | −16.89*** | −5.405*** | −0.0128 | 0.0196 |
| $lnsig2u$ | 2.713*** | 0.514 | 3.905*** | 1.873*** | | |
| $N$ | 2756 | 1696 | 2756 | 1696 | 2756 | 1696 |

Table 2.4: Probit, Logit and LPM Regressions for Republican and Democratic States

Note: dependent variable is the probability of an SIP order. *, ** and *** denote significant at 5%, 1% and 0.1% levels. *Dem* is Democratic and *Rep* is Republican. The LPM regression contained state-level fixed effects.

variable is the probability of state $i$ with no SIP order introducing an SIP order on day $t$, $\Pi_{i,t}$.

$$\Pi_{i,t} = a_i N_{D,SIP,t} + b_i N_{R,SIP,t} + c_i N_{S,SIP,t} + d_i NC_{i,t} + K_i + \epsilon_{i,t} \tag{2.7}$$

Here $N_{D,SIP,t}$ is the fraction of democratic states that already have SIP orders in effect on day $t$, with similar interpretations for $N_{R,SIP,t}$ (republican) and $N_{S,SIP,t}$ (swing). $NC_{i,t}$ is the number of new cases per 100,000 of population in state $i$ on day $t$, $K_i$ is a constant and $\epsilon_{i,t}$ an error term. This approach assumes that the probability of implementing an SIP policy is independent of whether or not there is a mask-wearing policy in place. In the appendix, where we conduct robustness checks, we allow the selection of an SIP policy to depend on whether there is a mask policy in place: the results show that it does not, and that this specification is robust. The results of estimating this equation by probit, logit and linear probabilities are given in Table 2.4.

The Probit and Logit models both show highly significant coefficients on all of the SIP shares for both democratic and republican states, though surprisingly republican states show negative coefficients on the share of swing states with SIP orders in place. The number of new cases is significant for democratic states but not for republican. Republican governors appear to be taking their leads from other states rather than from the number of their resident contracting COVID-19.

To assess the impact of a change in one state's policies on the choice made by another, we need to calculate the marginal effect of a change in an independent variable on the probability of implementing an SIP policy. In the tables that follow we set the variables other than the SIP rate with respect to which we are differentiating equal to either their sample means or their maximum values, and report the marginal effect for all possible SIP rates. The first column in Table 2.5 shows $N_{D,m,t}$ the democratic SIP rate, the second the probability of an SIP policy being implemented in a democratic state without such a policy according to the probit model, the third the change in probability (the marginal effect), the fourth and fifth columns the same for a republican state, and the remaining columns repeat this for the logit model. Overall this table shows the effects of changes in the fraction of democratic states with SIP orders on the probability that a democratic or republican state without such an order will change, with other independent variables at their mean values. For republican states this effect is zero: for democratic states it is positive. According to the logit analysis, once 69% of democratic states have adopted SIP orders, then with probability one all others will follow suit. The probit analysis does not indicate a tipping point in this case: the probability of a state without an SIP order choosing such an order only reaches one when the fraction of states with SIP orders is also one.

Table 2.6 shows a similar analysis for the marginal effect of a change in the fraction of republican states with SIP orders, with other independent variables again at their mean values. In this case the increase in the number of republican states with SIP orders tips the democratic states without such orders once the fraction of republicans with SIP orders exceeds 0.61 in the probit regression and 0.53 in the logit. It is interesting that an increase in the number of republican states with SIP orders can tip the democratic states into following suit. We do not see this cross-party effect in the case of mask-wearing orders, studied above. It may indicate that mask-wearing is more politically contentious.

Table 2.7 shows a similar effect going the other way - the effect of democratic states' choices on republican states' choices, when other independent variables are set in this case at their maximum values. In this case the probability of a republican state adopting an SIP order only reaches one when all democratic states have already adopted such orders. Recall from Table 2.5

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{D,SIP,t}$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ |
| 0.000 | 0.36 | | 0.00 | 0.00 | 0.51 | | 0.00 | 0.00 |
| 0.0625 | 0.42 | 0.06 | 0.00 | 0.00 | 0.62 | 0.11 | 0.00 | 0.00 |
| 0.1250 | 0.55 | 0.07 | ” | ” | 0.72 | 0.10 | ” | ” |
| 0.1875 | 0.61 | 0.06 | ” | ” | 0.80 | 0.08 | ” | ” |
| 0.3125 | 0.67 | 0.06 | ” | ” | 0.87 | 0.07 | ” | ” |
| 0.3750 | 0.73 | 0.06 | ” | ” | 0.92 | 0.05 | ” | ” |
| 0.4375 | 0.78 | 0.05 | ” | ” | 0.95 | 0.04 | ” | ” |
| 0.5000 | 0.82 | 0.04 | ” | ” | 0.97 | 0.02 | ” | ” |
| 0.5625 | 0.86 | 0.04 | ” | ” | 0.99 | 0.02 | ” | ” |
| 0.6250 | 0.9 | 0.04 | ” | ” | 0.99 | 0.01 | ” | ” |
| 0.6875 | 0.92 | 0.02 | ” | ” | 1.00 | 0.00 | ” | ” |
| 0.7500 | 0.94 | 0.02 | ” | ” | ” | ” | ” | ” |
| 0.8125 | 0.96 | 0.02 | ” | ” | ” | ” | ” | ” |
| 0.8750 | 0.97 | 0.01 | ” | ” | ” | ” | ” | ” |
| 0.9374 | 0.98 | 0.01 | ” | ” | ” | ” | ” | ” |
| 1.0000 | 0.99 | 0.01 | ” | ” | ” | ” | ” | ” |

Table 2.5: Marginal Effect of Change in Democratic SIP rate

Note: other independent variables set equal to sample means.

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{R,SIP,t}$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ |
| 0.000 | 0.62 | | 0.00 | 0.00 | 0.60 | | 0.00 | 0.00 |
| 0.03846 | 0.67 | 0.06 | 0.00 | 0.00 | 0.68 | 0.08 | 0.00 | 0.00 |
| 0.07692 | 0.72 | 0.07 | ” | ” | 0.75 | 0.07 | ” | ” |
| 0.11538 | 0.77 | 0.06 | ” | ” | 0.81 | 0.068 | ” | ” |
| 0.19231 | 0.81 | 0.06 | ” | ” | 0.86 | 0.05 | ” | ” |
| 0.23077 | 0.84 | 0.06 | ” | ” | 0.90 | 0.04 | ” | ” |
| 0.26923 | 0.87 | 0.05 | ” | ” | 0.92 | 0.02 | ” | ” |
| 0.30769 | 0.90 | 0.04 | ” | ” | 0.95 | 0.03 | ” | ” |
| 0.34615 | 0.92 | 0.02 | ” | ” | 0.96 | 0.01 | ” | ” |
| 0.38462 | 0.94 | 0.02 | ” | ” | 0.97 | 0.01 | ” | ” |
| 0.42308 | 0.95 | 0.01 | ” | ” | 0.98 | 0.01 | ” | ” |
| 0.46154 | 0.97 | 0.02 | ” | ” | 0.99 | 0.01 | ” | ” |
| 0.53846 | 0.98 | 0.01 | ” | ” | 0.99 | 0.00 | ” | ” |
| 0.57692 | 0.99 | 0.01 | ” | ” | 1.00 | 0.01 | ” | ” |
| 0.61538 | 0.99 | 0.00 | ” | ” | 1.00 | 0.00 | ” | ” |
| 0.65385 | 1.00 | 0.00 | ” | ” | 1.00 | 0.00 | ” | ” |

Table 2.6: Marginal Effect of Change in Republican SIP Rate

Note: other independent variables set equal to sample means.

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{D,SIP,t}$ | *Prob* | Δ | *Prob* | Δ | *Prob* | Δ | *Prob* | Δ |
| 0.000 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| 0.0625 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| 0.1250 | ” | ” | 0.01 | 0.01 | ” | ” | 0.01 | 0.01 |
| 0.1875 | ” | ” | 0.03 | 0.02 | ” | ” | 0.01 | 0.01 |
| 0.2500 | ” | | 0.07 | 0.03 | ” | | 0.02 | 0.01 |
| 0.3125 | ” | ” | 0.13 | 0.06 | ” | ” | 0.05 | 0.02 |
| 0.3750 | ” | ” | 0.22 | 0.09 | ” | ” | 0.09 | 0.04 |
| 0.4375 | ” | ” | 0.33 | 0.12 | ” | ” | 0.16 | 0.07 |
| 0.5000 | ” | ” | 0.47 | 0.14 | ” | ” | 0.27 | 0.11 |
| 0.5625 | ” | ” | 0.61 | 0.14 | ” | ” | 0.41 | 0.15 |
| 0.6250 | ” | ” | 0.74 | 0.13 | ” | ” | 0.58 | 0.16 |
| 0.6875 | ” | ” | 0.84 | 0.10 | ” | ” | 0.73 | 0.15 |
| 0.7500 | ” | ” | 0.91 | 0.07 | ” | ” | 0.84 | 0.11 |
| 0.8125 | ” | ” | 0.96 | 0.04 | ” | ” | 0.91 | 0.07 |
| 0.8750 | ” | ” | 0.98 | 0.02 | ” | ” | 0.95 | 0.04 |
| 0.9375 | ” | ” | 0.99 | 0.01 | ” | ” | 0.97 | 0.02 |
| 1.0000 | ” | ” | 1.00 | 0.00 | ” | ” | 0.99 | 0.01 |

Table 2.7: Marginal Effect of Change in democratic SIP rate

Note: other independent variables set equal to maximum values.

that when other independent variables are set at the sample means, a change in the number of democratic states with SIP orders has no impact on the probability of a republican state adopting such an order.

In Table 2.8 we look at the case of other independent variables at their maximum values and the republican adoption rate varying. In this case the democratic states are already choosing SIP orders with probability one. The republican states tip at a fraction 0.69 (probit) or 0.61 (logit).

Tables 2.5 through 2.8 show how the chances of a democratic or republican state choosing an SIP policy vary with the number of other states that already have such a policy in place, holding all other independent variables at either their mean or maximum values. The space of independent variables is four dimensional (three policy rates and the number of new cases), so we are looking at the response of probabilities along a one-dimensional subspace in this four-dimensional space.

| | *Probit* | | | | *Logit* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Democratic* | | *Republican* | | *Democratic* | | *Republican* | |
| $N_{R,SIP,t}$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ | *Prob* | $\Delta$ |
| 0.000 | 1.00 | | 0.00 | 0.00 | 1.00 | | 0.00 | 0.00 |
| 0.03846 | 1.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 |
| 0.07692 | ” | ” | 0.01 | 0.01 | ” | ” | ” | ” |
| 0.11538 | ” | ” | 0.02 | 0.01 | ” | ” | ” | ” |
| 0.15385 | ” | ” | 0.04 | 0.02 | ” | ” | | |
| 0.19231 | ” | ” | 0.08 | 0.04 | ” | ” | ” | ” |
| 0.23077 | ” | ” | 0.14 | 0.06 | ” | ” | 0.00 | ” |
| 0.26923 | ” | ” | 0.23 | 0.08 | ” | ” | 0.02 | 0.01 |
| 0.30769 | ” | ” | 0.33 | 0.11 | ” | ” | 0.06 | 0.04 |
| 0.34615 | ” | ” | 0.46 | 0.12 | ” | ” | 0.17 | 0.11 |
| 0.38462 | ” | ” | 0.59 | 0.13 | ” | ” | 0.35 | 0.18 |
| 0.42308 | ” | ” | 0.71 | 0.12 | ” | ” | 0.58 | 0.23 |
| 0.46154 | ” | ” | 0.81 | 0.10 | ” | ” | 0.79 | 0.20 |
| 0.53846 | ” | ” | 0.93 | 0.13 | ” | ” | 0.98 | 0.19 |
| 0.57692 | ” | ” | 0.97 | 0.03 | ” | ” | 0.99 | 0.02 |
| 0.61538 | ” | ” | 0.98 | 0.02 | ” | ” | 1.00 | 0.00 |
| 0.65385 | ” | ” | 0.99 | 0.01 | ” | ” | 1.00 | 0.00 |
| 0.69231 | ” | ” | 1.00 | 0.00 | ” | ” | 1.00 | 0.00 |

Table 2.8: Marginal Effect of Change in Republican SIP Rate

Note: other independent variables set equal to maximum values.

Clearly this can give only very limited insights into the relationships between dependent and independent variables.

In Figure 2.3 we explore the response of probabilities of choosing an SIP policy to independent variables in a more multidimensional way, looking at two-dimensional subspaces of the four-dimensional space of independent variables. We vary the SIP rates for democratic, republican and swing states, holding the rate of new COVID-19 cases constant at its mean value. Figure 2.3 shows on the horizontal axes the percentages of swing and republican states adopting SIP policies (red = republican, blue = democratic), on the vertical axis the probability of a democratic state that has not adopted an SIP policy doing so, with the percentage of democratic states that have SIP policies in place increasing from top left to lower right, going from 0% to 18% then 43% and ending at 63%. Each of these figures is a two-dimensional slice of the four-dimensional space of independent variables, in the plane defined by the SIP adoption rates of swing and republican states. The adoption rate of the democratic states varies from one panel to the next, so taken together they are part of a three-dimensional subspace of the space of independent variables.

The figures show the probability increasing with increases in the percentages of swing and republican states that have already adopted, and also increasing with the percentage of democratic states that have already adopted. All four figures show that when the percentages of swing and republican states are zero, the probability of a democratic state adopting is zero, however many such states have already adopted. They also show that for low levels of democratic adoption (0% and 18%, the first two figures) the probability is relatively insensitive to the swing state adoption rate, whereas for higher values of democratic adoption the swing states can drive bigger changes in the democratic probability of adoption. Comparing the first and last figures, corresponding to blue $SIP = 0\%$ and $SIP = 63\%$, it is clear that the probability of adoption has risen substantially for low values of the percentages of swing and republican states with SIP policies in place. Tables 2.5 to 2.8 show one-dimensional slices through Figure 2.3, taken vertically at the mean or maximum values of the variables on the horizontal axes and the case rate.

Figure 2.4 shows the same information for republican states. The probability of choosing

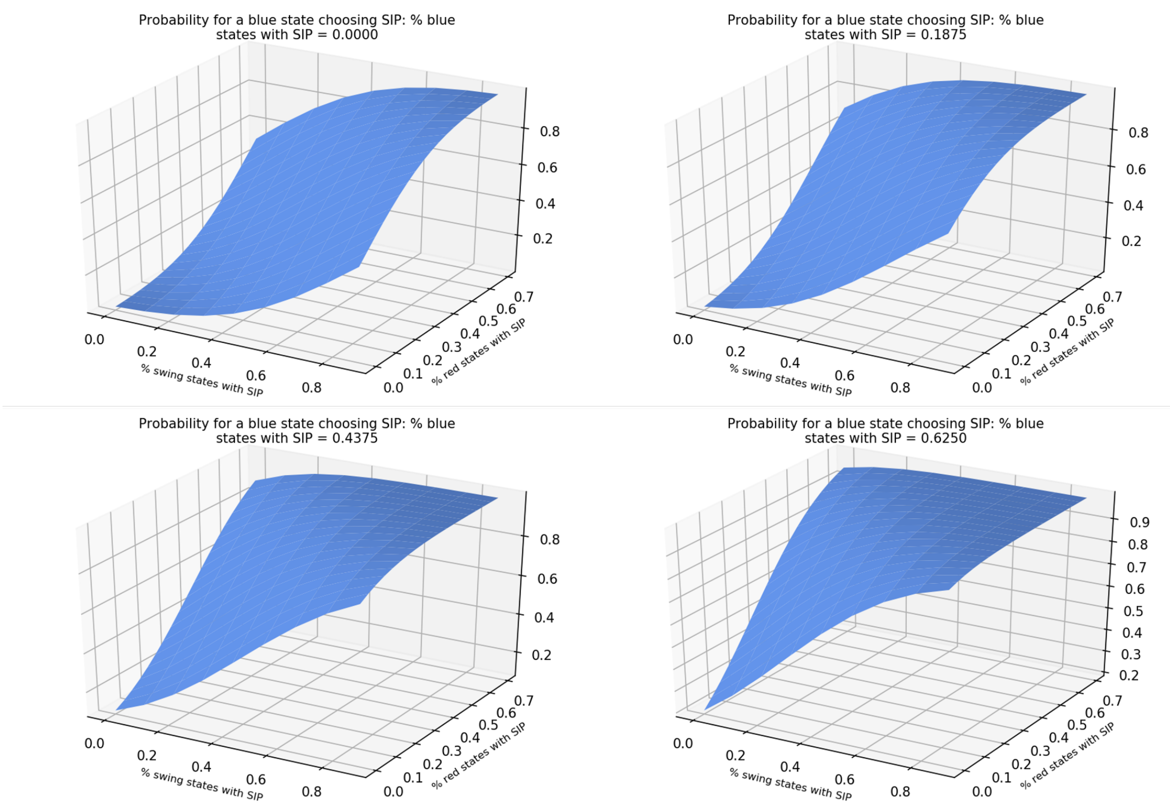



Figure 2.3: Democratic SIP Response to Other States' Choices

an SIP policy is much less - the surface is uniformly lower than in the democratic cases - and decreases rather than increases with the percentage of swing states choosing an SIP policy, reflecting the negative regression coefficient on swing state adoption rates in Table 2.4. In general other states (swing, democratic) seem to have less influence on republican choices than they do with democratic choices.

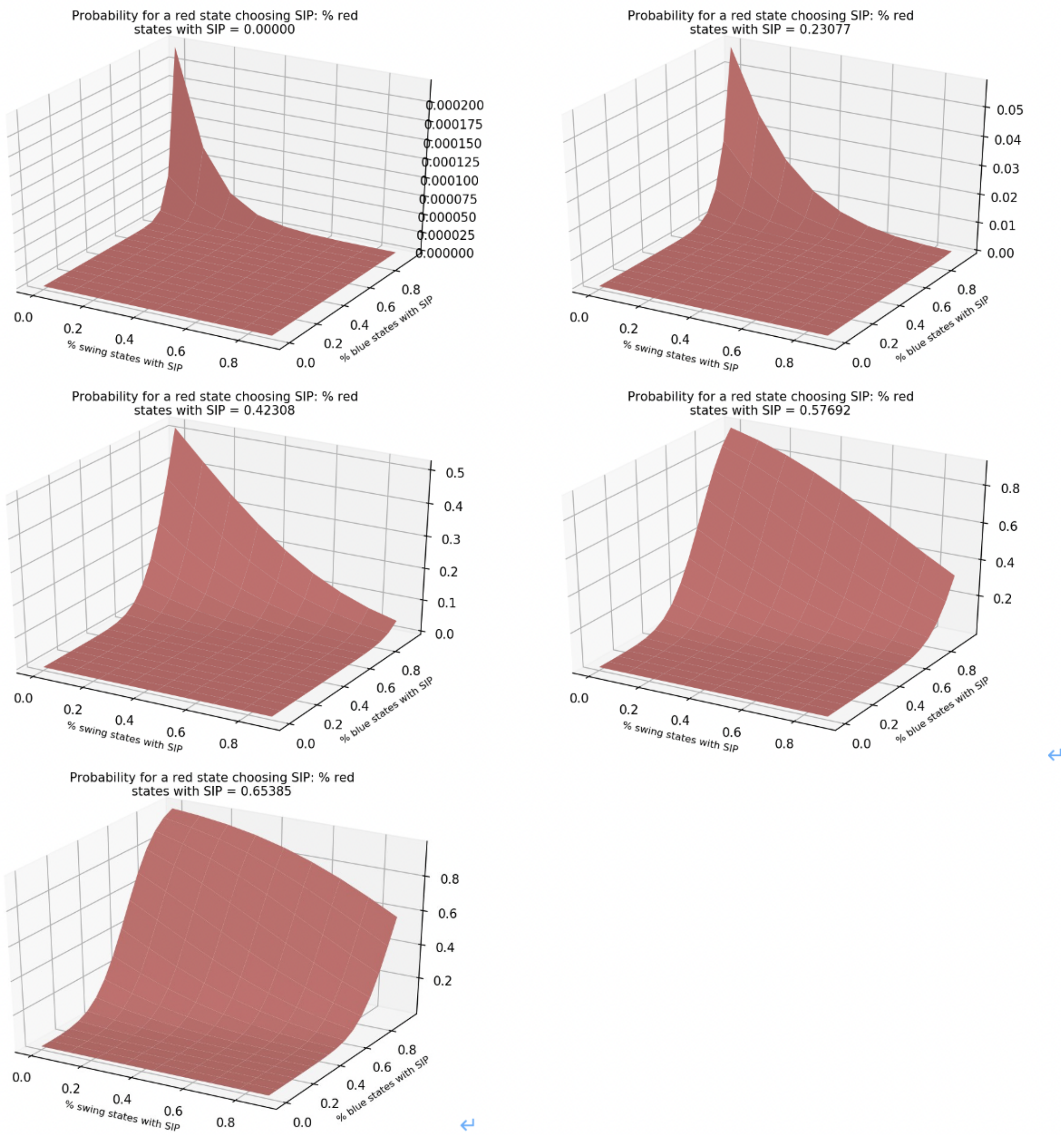



Figure 2.4: Republican SIP Response to Other States' Choices

## 2.4 Discussion

### 2.4.1 Empirical Challenges

The reflection problem (Brock and Durlauf 2001; Lee et al. 2014; Manski 1993) in a Probit/Logit estimation of peer effects may be influential for our estimation. The idea is that when we estimate a model like Equation 2.6, the significance of the estimated parameters $\alpha, \beta$ and $\gamma$ may come from two sources: either the true peer effects (tipping) or some common state-of-the-world contexts. For instance, since severity and economic shocks are geographically correlated, it is ambiguous whether some common epidemiological or socioeconomic factors instead of tipping set effects are determining the results. Also, the real-world spatial interdependence is actually more complicated than the partisanship effect discussed in the body of the paper. For instance, our model setup implied that Oregon had the same impact on California and New York, which is unlikely to be satisfied in the real world.

To cope with the problem, a strategy is to take some the socioeconomic controls in neighboring states in addition to the state of interest $i$. Note that to use the severity of neighbors may not be a good strategy, as the severity might directly and dynamically impact the decisions of SIP or masks in other states. Another strategy is to follow a recent network economics paper (Zhou 2019). In this paper, the social interaction matrix between states could be heterogeneous, and we can use a spatial version of that model in better estimating our model, simultaneously coping with the reflection and the spatial interdependence problem. For example, we may say that both political affiliation and geographically proximity contribute to the matrix: thus, we can make the value of the NY-NJ proximity 2, NY-PA (politically different but adjacent) or NY-CA (politically same but not adjacent) 1, and NY-ND 0.

### 2.4.2 Further Discussion

Shelter-in-place strategies and mask-wearing are integral to overcoming a pandemic. In the U.S., these strategies have to be implemented by states, which face complex combinations of economic and political costs and benefits from their possible choices. Their decisions are affected by those of other states since strategy choices demonstrate social and political reinforcement. A compelling illustration of this interdependence is the interactions between New York and its neighboring states: the tri-state region can be seen as a single unit in terms of employment, commuting, entertainment and retail shopping. A move towards SIP orders or compulsory mask-wearing by any of these states will affect the other two, and its effectiveness will depend on the reactions of the others. Because of this, we can model their choices as a game. Specifically, we show that the choice of a policy by a single state or a group of states may tip a system to a new Nash equilibrium at which many more agents have adopted shelter-in-place or social distancing policies. It could also cause a cascade from one equilibrium to another. There may be equilibria at which all democratic states adopt such policies while no republicans do, and a subset of democratic states may tip its fellows into adopting these policies, while a subset of republican states may tip their fellows into dropping or adopting these policies.

Our empirical work on the introduction of shelter-in-place orders or mask-wearing confirms that the choices of one state influence strongly those of others, and that in several cases this interaction is powerful enough to lead to tipping to the universal adoption of a policy by one category of states. In general the strongest interactions are between states of the same political orientation, but there are cases when democratic states are strongly influenced by republican states and by swing states, and republican states influenced by swing states. Republican states are influenced little by the actions of democratic states. The number of new COVID-19 cases also has an impact on the states' choices in some cases, albeit a small one. The choice of mask-wearing policies appears to be far more sensitive to the actions of other states than the choice of SIP policies. Republican states far more reluctant than democratic to adopt either SIP or mask-wearing policies. Overall, responses to the greatest public health challenge the US has faced in a century have been shaped more by political considerations than by public health requirements.

While we find substantial support for the theoretical framework set out in the theoretical sections, we do also note differences between the factors determining the choices of mask-wearing policies and SIP policies. There is clearer evidence of tipping in the case of mask-wearing: a state's choice of mask-wearing policies responds more sharply to changes in the choices made by other states than the choice of an SIP policy. This is shown very clearly in the differences between figures 2.1 and 2.3. In the former there is a sharp transition from low to high probability of implementing a policy: this is not true in the latter. There are also differences between the responses of democratic and republican states - as evidenced by the contrasts between Figures 2.1 and 2.2, and between 2.3 and 2.4. There is essentially no part of the space of independent variables where the democratic SIP probability is zero, whereas there are large parts for which this is true in the republican case.

As we noted above, the contrast between responses on mask-wearing and SIP policies is predictable on the basis of arguments made in the previous Chapter. There we argue that SIP has a real economic cost for anyone who cannot work from home (Thunström et al. 2020). Hence it is opposed by economically vulnerable populations.[10] Mask-wearing, in contrast, has no economic cost: it can however be seen as a signal. Not wearing a mask was adopted as a signal of support for Trump and skepticism about the importance of COVID-19 and the appropriateness of policy measures aimed at it: mask-wearing has become heavily politicized. This suggests that the factors that influence choices about enacting policies are different in the two cases, with economic factors weighing more heavily in SIP choices and political/symbolic factors more important in mask-related policies. The evidence in the first chapter clearly supports this.

This can explain democratic-republican differences. Republican states are more likely to contain economically vulnerable populations who stand to lose from SIP policies and so will be more reluctant to such policies: contrast Figure 2.3 with 2.4. And republican states can also be expected to be less receptive to mask-wearing because of its symbolism, a point that is confirmed by the differences between Figures 2.1 and 2.2, where the probability of a republican state adopting a mask-wearing policy is low whatever the values of the independent variables. For democratic states there is always a part of the independent variable space where this probability is large.

As of late 2020, states have had access to vaccines against COVID-19 and have had to set

[10] Economically vulnerable populations are those who cannot work from home, who have limited savings and whose states have limited social safety nets.

vaccination priorities. There may also be an element of social reinforcement in the choice of vaccination strategies, so the framework we have developed here may be applicable in that context too.

# Chapter 3: The Economics and Psychology of Personality in China

This paper explores the unique structures, formation mechanism, and economic impacts of personality traits in China. Using a longitudinal twin dataset in Yunnan Province, we reach the following conclusions: (1) We find evidence for orthogonality in reporting socially desirable and undesirable traits in China, leading to a failure of the Five Factor Model. We detect a unique dialectical 6-factor personality structure in which three desirable and three undesirable traits coexist in an orthogonal manner. Desirable traits can be decomposed into Social Desirability, Extraversion and Openness, and undesirable traits into Disorderliness, Neuroticism and Introversion. (2) The genetic heritability of personality trait is significantly lower in China than Western countries, and the effect of shared environment is much larger. Nurture may dominate nature in Chinese personality. (3) Using a within-twin design, we show that personality has a significant causal effect on individual economic outcomes and preferences, including education performance, income, subjective well-being and risk attitudes. Specifically, we find evidence that Social Desirability is associated to lower income and Extraversion is associated to higher income, especially for women.

## 3.1 Introduction

Is personality a key determinant of lifelong economic outcomes? Though having been asked for thousands of years in both the West and the East, the question about how personality impacts life outcomes remains a fresh topic. With the development of interdisciplinary methodology, economists have now taken personality into increasingly serious account and gained intense interest in studying the intersection of personality and economic behaviors. [1]

[1] As Nobel Prize Laureate James Heckman and peers documents, "There is a lot of room for cooperation and exchange of findings and methods between personality psychology and economics, ... , Personality traits are predictive of socioeconomic success. They can be influenced by interventions and investment more readily than IQ, at least after the early years (Almlund et al. 2011; Borghans et al. 2008).

Systematic study on this topic, as related literature (Almlund et al. 2011; Borghans et al. 2008; Heckman et al. 2019) suggest, involves progress on the following issues:

(1) Understanding personality structure, including measurements of personality, separation of personality from cognitive skills, reliability and validity tests, etc.

(2) Understanding personality formation and development, including studying the lifelong stability and genetic heritability of personality, and to what extent personality can be influenced by investment and interference.

(3) Understanding the "ceteris paribus" causal effect of personality on economic behaviors, including preferences, choices and outcomes, and therefore quantifying the importance of personality-related enrichment for current economic models and policy.

These three aspects can be briefly summarized as "structures, formation and impacts" of personality. In this paper, we study these questions in China. We are the first to comprehensively study the economics of personality traits in China, and the first to incorporate cultural psychology to the economic research of personality traits.

This paper studies the economics and psychology of personality traits in China with a cross-cultural perspective. Previously, most personality studies, especially the intersection of personality and economics, were taken place in "WEIRD" (Western, Educated, Industrialized, Rich and Democratic) countries, and it is widely argued that such findings may be less universal in Eastern culture or developing countries (Heine 2015; Henrich et al. 2010a,b; Laajaj et al. 2019; Nisbett et al. 2001). Therefore, when studying personality problems in China, we expect various cultural, psychological and economic reasons to doubt that typical Western findings and models [2] will still hold in China. Even current studies in Japan or Korea is not sufficient; when we come to the intersection of personality and economics, the crucially different economic development level, political institutions and social expectations may still make China distinctive. Furthermore, personality data is much less prevalent and systematically measured in China than the West or Japan, resulting in a large gap on understanding of this topic.

[2] These parts will be summarized in the following parts of the paper.

The importance of enriching economic models by personality psychology, the lack of local studies, and the crucial cultural and socioeconomic distinction, jointly highlight the necessity of a comprehensive study of personality and economics in China. [3]

Conceptually, personality structures in China might differ substantially between China and other countries, especially the WEIRD ones. First, self construal in China is interdependent (Kitayama and Markus 1999; Markus and Kitayama 1991), meaning that self-concepts are built by social roles and relationships, in contrast to the independent self that is typical in Western culture. The interdependent self comes from social expectations and conditions that expect people's behaviors are highly flexible, fitting in different scenarios. This is fundamentally different from the West where people are expected to have self-consistency across situations (Kanagawa et al. 2001; Nisbett 2004; Nisbett et al. 2001), and systematically impacts the formation of personality structures and response to assessments (Schmitt et al. 2007). [4] Specifically, as (Nisbett 2004) argues that, Barnum effects (the tendency to report high in all questions) are much more prevalent for East Asians than Western people. This is because East Asians may comfortably report high in questions that have some opposite meaning, but similar responses will "appear improbable, illogical, or even irrational in most Western nations" (Spencer-Rodgers et al. 2004, 2010b). In other words, East Asians' self concepts are relatively flexible; they do not see a necessary contradiction between "A" and "not A" in themselves. In self-reports of esteem (Choi and Choi 2002), self-concepts (Boucher 2011; Spencer-Rodgers et al. 2009, 2004), and emotions (An et al. 2017; Miyamoto and Ryff 2011; Spencer-Rodgers et al. 2010a), the dialectical thoughts are relatively common for East Asians. Dialectical responses will significantly impact the correlation structures of the items; for instance, if people reply to a regular item (such as "I am talkative") and a reversed item (such as "I am quiet") with zero or even positive correlation, the personality constructs are essentially different. These cultural psychological properties are crucial to understand the dynamics of personality in China, and leads to the first part of our study in which we assess the use of existing

[3] Details of historical perspectives are discussed in the appendix.

[4] This social expectation effect fits in the theory of Rosenthal Effect, or Pygmalion Effect (Rosenthal and Rubin 1982))

tools for personality assessments from a cross-cultural perspective.

Lay beliefs of ancient China also advocate for dialectical personality. Chinese people believe that the elements of "Junzi" (Good) and "Xiaoren" (Bad) may exist simultaneously in every person, and whether an individual is "Junzi" or "Xiaoren" is dependent on her choice at certain situations. A famous quote by Li Shimin (The first Emperor of Tang Dynasty) says: "Whether a man is Junzi or Xiaoren is not constant. Doing good makes him Junzi and doing bad makes him Xiaoren." This indicates that in ancient China, it is widely perceived that the elements of positive and negative traits are dwelling in the same individual, and they can coexist in harmony. This is a typical representation of a more flexible, situation-based self concept versus a consistent, situation-independent one in the West (Kanagawa et al. 2001; Spencer-Rodgers et al. 2009).

In the developed world, The Five Factor Model (FFM) [5] is the most well accepted methodology to describe personality. These factors are often referred to as the Big Five Personality Traits. The FFM states that human personalities can be characterized using five relatively independent factors: Openness to Experience, Conscientiousness, Extraversion, Agreeableness and Neuroticism (Emotional Stability). In the past few decades, most research in the West and Japan suggests a consistent validity of the Big Five Personality structure. However, deviance from the Big Five is not a anomaly in developing countries (Laajaj et al. 2019; Yoon et al. 2002).

In China, evidence favoring and challenging the Big Five is mixed. Yang et al. 1999 studied the NEO-PI-R (a typically used version of the Big Five questionnaires), and found that the five-factor structure is recovered within a large psychiatric sample in China, and many projects follow this setup and keep using the Big Five in China. However, there exist considerably many studies showing that the Big Five structures are missing, or it is necessary to add China-specific traits (Cheung et al. 2003; Cheung and Leung 1998; Cheung et al. 2001; Wang et al. 2005; Zhou et al. 2009). It is worthwhile to specifically mention a recent study that uses the same inventory (BFI-44) as we do (Carciofo et al. 2016), and ends up with generally supporting the Big Five while finding relatively low internal consistency within the Big Five factors and suggesting that most

[5] Allik and Allik 2002; Costa and McCrae 1985; Costa Jr and McCrae 1992; Digman 1990; Goldberg 1990; McCrae and Costa 1987; McCrae and Costa Jr 1997; Wiggins 1996

*reversed items* do not perform well. Indeed, the "missing reversed items" is *not* likely to be a coincidence and seems a typical result of dialectical personality, despite that this study does not go further. In our study, we explore deeply into this pattern and resolve the current conflicts in the literature by formally reinterpreting personality in China with a dialectical perspective.

Given the rich literature and social beliefs about dialectical thinking in China/East Asia, it is surprising that in the FFM literature in Asia, no formal research has discussed about the role of dialectical thinking, and this is what this paper does. In this paper, we derive a dialectical personality model from the Big Five Inventory and show the similarities and discrepancies of this model from traditional FFM. We find that we need to independently treat "good" and "bad" traits as two orthogonal categories, each of which includes three factors. The combination of "good" traits are denoted as General Confidence, including *Social Desirability*, *Extraversion* and *Openness*; and the combination of "bad" traits as General Weakness, including *Disorderliness*, *Neuroticism* and *Introversion*. We discuss about details of this construction, test the reliability and validity, and compares with the FFM model in terms of predictive power. We find that a dialectical model generally performs better than the FFM.

We next turn to personality formation. Current research on personality formation studies how genes, shared family environments, education, life events, and exogenous interference influence personality development. Also, it studies the stability of traits over a lifespan. In the personality psychology community, researchers have been reaching a consensus which may surprise economists and other practitioners; personality is mostly genetic (the genetic heritability is around 50%, and the effect of family environment is very limited, even close to 0[6]. This conclusion are mainly reached through behavioral genetics, especially twin studies (Plomin 2019; Polderman et al. 2015; Tellegen et al. 1988; Vukasović and Bratko 2015). However, behavioral genetics studies are surprisingly rare in the East. In Japan there are a few findings showing that the heritability of personality is slightly lower than that in the West (Kawamoto and Endo 2015; Ono et al. 2000;

[6] "We would essentially be the same person if we had been adopted at birth and raised in a different family. Environmental influences are important, accounting for about half of the differences between us, but they are largely unsystematic, unstable and idiosyncratic"– in a word, random." Says Robert Plomin, in a recent book on behavioral genetics (Plomin 2019)

Yamagata et al. 2006) but the heritage processes are indeed comparable to the West.

In China, however, there is literally no existing behavioral genetics study of personality, and due to the potential uniqueness of China, we have no reason to believe that all Western stories and even the Japanese ones will automatically apply in China.

First, compared to countries where behavioral genetics studies are done, most regions in China (especially before 2015) are still in a relatively underdeveloped socioeconomic status, leading to a large variance of socioeconomic status across families. This is fundamental for behavioral genetic studies, since socioeconomic status is proven to be a crucial moderator for trait inheritance. As sociogenomic studies (Briley and Tucker-Drob 2014; Roberts and Jackson 2008) suggests, how biological factors function is not unchangeable, and the heritability is not always 50% (Krueger et al. 2008). Shared environmental effects can be larger in families that are less developed or experiencing more conflicts. Indeed, there is a larger literature suggesting that in underdeveloped areas or poorer families, traits, such as IQ, has a much lower heritability and a higher shared environmental effect (Henrich et al. 2010b; Rowe et al. 1999; Turkheimer et al. 2003), and the major reason is that family environments have much larger variances (Nisbett 2009). Specifically, Henrich et al. In a recent study it is explicitly argued that a high heritability of IQ is a typical WEIRD conclusion, which is a fair analogy with personality (Henrich et al. 2010b).

Furthermore, historical and cultural reasons may also significantly impact formation of personality in China. In China, personality has been long regarded as a nurture thing, and especially, family environment is what matters. The family pushes the child to develop according to social expectations.[7]he uniform social belief of the impact of strict and conscientious family education on personality development have formed a culture of heavy parental intervention during the childhood, which may lead to a higher variance due to nurture. On the contrast, in the West

[7]For instance, the "Three-Character Canon" is one of the entry-level classics that is a requirement for almost all Chinese students who want to pursue further studies. It begins with this: "Man on earth, good at birth. The same nature, varies on nurture." These quotes indicate three important beliefs of the ancient Chinese about personality formation: the nature-based variance of personality is thin; the nature of personality is good; and the nurture-based variance is relatively large. Specifically, the Chinese culture emphasizes the primary importance of family environments. This motivates families to favor an authoritative parent-child relationship (Chao 1994; Chen et al. 1997; Kelley and Tseng 1992). "A tough father fosters a dutiful son but a kind mother makes a wastrel. "

where "Always be yourself, express yourself, have faith in yourself, do not go out and look for a successful personality and duplicate it" is encouraged, we have more reason to believe that personality is developed more freely by nature.

Finally, the highly interdependent thinking style and collectivist culture in China may make personality a societal concept rather than an individual one (Markus and Kitayama 1998). This may also lower the heritability estimates of personality because it is found that social interaction styles are a less heritable trait (Polderman et al. 2015).

All the information above leads to our expectation that personality may largely rely on shared environmental effects (nurture) in China. For many traits, the genetic component is almost 0, while the shared environmental effect is substantially larger at 40%-60%. These findings robustly suggest a crucial role of shared environmental effect in personality formation in China.

Last but not least, we go to personality impacts, especially on economic outcomes and behaviors. The economic impacts of personality are a recently emerging topic driven by economists and psychologists. Generally, these studies are divided into two categories: personality-preference, and personality-outcomes. The first category focuses on studying how personality traits are related with economic preferences. The current literature trying to link them generates mixed results (Almlund et al. 2011; Becker et al. 2012; Dean and Ortoleva 2019; Jagelka 2019), suggesting that personality may be valuable to be separated out as distinctive aspects to enrich economic models and better understand human decisions (Heckman et al. 2019). The other category is about causal inference of personality traits on economic outcomes. Like for other topics, reversed causality, measurement error and omitted variable problems are three important endogeneity problems for economists to establish causal relationships between personality and economic outcomes. The problem of reversed causality lies in self-reports: it is possible that the economic outcomes are influencing subjective welfare, and therefore report differently. Measurement errors are also typical in self-reports. To minimize this error, any construction of psychometric indicators requires careful psychometric methods. Omitted variable problem is also typical, since personality may be correlated with some unobserved heterogeneity of family backgrounds or intellectual endowments.

In this paper, twin data allows us to do within-twin analysis to better test how personality impacts economic outcomes and get rid of many potential sources of omitted variable biases.

The effect of personality traits on economic outcomes is also mediated by culture. One important pathway is through social expectations. In traditional Chinese culture, conscientiousness and agreeableness are regarded as socially desirable traits; while extraversion and openness are not emphasized. In Confucianism, self-control (Ke Ji), ritual obedience (Fu Li), and altruism or philanthropy (Ai Ren) are regarded as fundamental for any social achievements, whether in family, in career development, or in political success. We can reasonably hypothesize that these traits (captured by *Social Desirability* in the dialectical personality model) may lead to better economic outcomes; however, these traits may also represent a tendency of sticking with Chinese traditions and beliefs, making the aggregated economic effect ambiguous.

In this part, we test the impacts of personality traits on many economic behaviors and outcomes. Most of our findings are comparable with Western findings; *Disorderliness* is bad for academic outcomes, *Openness* decreases risk aversion, and *Extraversion* leads to better subjective well-being. However, in contrast to previous Western findings, we find that *Social Desirability* leads to *lower* temporary income, especially for women. Detailed mechanisms are discussed.

This paper systematically studies the structures, formation, and economic impacts of personality traits in China, and we detect robustly large difference in China from widely acknowledged Western findings.

The major difference lies in personality formation and structures. First, the lack of genetic component of personality formation is mostly likely due to the large variance of socioeconomic status across families, strong parental and social intervention, and the interdependence style of self formation. Second, the unique structures of personality may come from various mechanisms. Synthesizing our results with the current literature, we propose that: the independence of positive and negative items, and contradictory descriptions come from dialectical thinking (Choi and Choi 2002; Peng and Nisbett 1999; Spencer-Rodgers et al. 2004); the difficulty to separate Conscientiousness, Agreeableness and Neuroticism may come from social expectations about a

"Desirable Personality"; and the significantly low representation of genetic components in personality formation may also contribute to the disappearance of the Big-Five structure.

Our paper has significant contribution to the literature in both methodological and empirical senses. Methodologically, we are the first to incorporate perspectives and concepts from cross-cultural psychology to explore the economics of personality and non-cognitive skills. This motivates future researchers on development economics, labor economics and behavioral economics to consider cross-cultural factors in approaching relevant problems in the developing world. Also, we are among the first to use twin study method to evaluate causal relationships between personality traits and economic variables. Empirically, we provide a systematic evaluation of the economics of personality in China and elaborates why it can be fundamentally different from that in the West, and offer many implications for research and policy. Personality structures suggests that it may be necessary to better localize the personality assessments in China for relevant studies applications. The difference in heritability suggests that Chinese parents may influence personality formation much more significantly than their Western counterparts, highlighting the importance of family-level personality education and development in China. The correlations and causality between personality and economic outcomes further support the implications above. Furthermore the fundamental difference of the Eastern and Western thinking sheds light on practice and research about development, international relations and political economy.

The remainder of this paper will be organized as follows. Section 2 discusses about our data and methodological framework. Section 3 discusses results in the order of personality structure, formation and impacts. Section 4 discusses about policy and application implications and future perspectives. Section 5 concludes.

## 3.2 Data and Methodological Framework

### 3.2.1 Data Source

In this paper, we mainly rely on Longitudinal Chinese Child Twin Survey (LCCTS). This survey has a large sample with around 4,000 people measuring personality. Also, this survey includes twins from both urban and rural residence, all born after one-child policy (Hong Chew et al. 2017). Having twin data allows us to fully explore the heritability of traits and use within-twin estimations to causally test the economic effects of personality traits.

Conducted by the Urban Survey Unit of the National Bureau of Statistics, the LCCTS is a two-wave, census-type longitudinal household survey, including data from both twin and non-twin families. The survey was first conducted from late 2002 to early 2003 in Kunming and surrounding areas in Yunnan Province, China. The age cohort of the twins was then 6 to 18. Then, a second wave was conducted from 2012 to 2014, with twins between 17 to 29 years old. Some of the twins had gotten a full time job by the time of second wave, and some were still students.

In the part of personality structures, we include all four categories of samples (twins, non-twins, and the parents of these groups). The total sample size is 3977. In the part of personality formation and impacts, we focus on same-sex twins (Tellegen et al. 1988; Vukasović and Bratko 2015). The total sample size is N=902 (456 pairs). Following (Li et al. 2010), we treat children with the same hair color, eye color, and appearance as Monozygotic (MZ). Accordingly, 192 pairs of twins are denoted as MZ and 264 pairs Dizygotic (DZ). In both samples, the sex ratio is close to 1:1.

### 3.2.2 Measurements of Personality Traits and Economic Variables

There are various self-reported measurements and outcomes in this paper, and it is necessary to fully explain how they are conducted and what they measure, especially for the self-reports.

#### Personality Inventory

This paper uses a standard Chinese version of 44-item Big Five Inventory (BFI-44) (Benet-Martinez and John 1998; John et al. 1991, 2008). As said on the official website of this test, "The Big Five Inventory (BFI) is a self-report inventory designed to measure the Big Five dimensions. It is quite brief for a multidimensional personality inventory (44 items total), and consists of short phrases with relatively accessible vocabulary." The original construction and item denotations of this inventory is shown as follows, and we will use the same denotation set in the following parts of this paper. All the questions are assessed based on a 5-point Likert scale, with (1) *strongly disagree* and (5) *strongly agree*.

| Dimension | Items | Regular Items | Reversed Items |
|---|---|---|---|
| Openness | 10 | 8(O5,O10,O15,O20,O25,O30,O40,O44) | 2(O35R,O41R) |
| Conscientiousness | 9 | 5(C3,C13,C28,C33,C38) | 4(C8R,C18R,C23R,C43R) |
| Extraversion | 8 | 5(E1,E11,E16,E26,E36) | 3(E6R,E21R,E21R) |
| Agreeableness | 9 | 5(A7,A17,A22,A32,A42) | 4(A2R,A12R,A27R,A37R) |
| Neuroticism | 8 | 5(N4,N14,N19,N29,N39) | 3(N9R,N24R,N34R) |
| Total | 44 | 28 | 16 |

Table 3.1: Original Construction of BFI-44

The full English and Chinese versions of this inventory can be retrieved in the appendix. The summary statistics will be discussed in detail in the personality structure part of this paper.

In the first-wave survey, parents are also asked to elicit their belief on children's strengths and weaknesses in a 20-item questionnaire. Questions include descriptions about agreeableness, attention, internalizing behaviors and externalizing behaviors.

### Cognitive Ability Measurements

In LCCTS, cognitive abilities are measured in two distinctive tests: a basic 6-question arithmetic test containing questions of elementary-school difficulty (For instance, "Two bottles of wine cost 3.1 yuan. How much do 12 bottles of wine cost?"), and a 10-question logical test asking subjects to identify the missing element which would complete the pattern. An example is shown here:

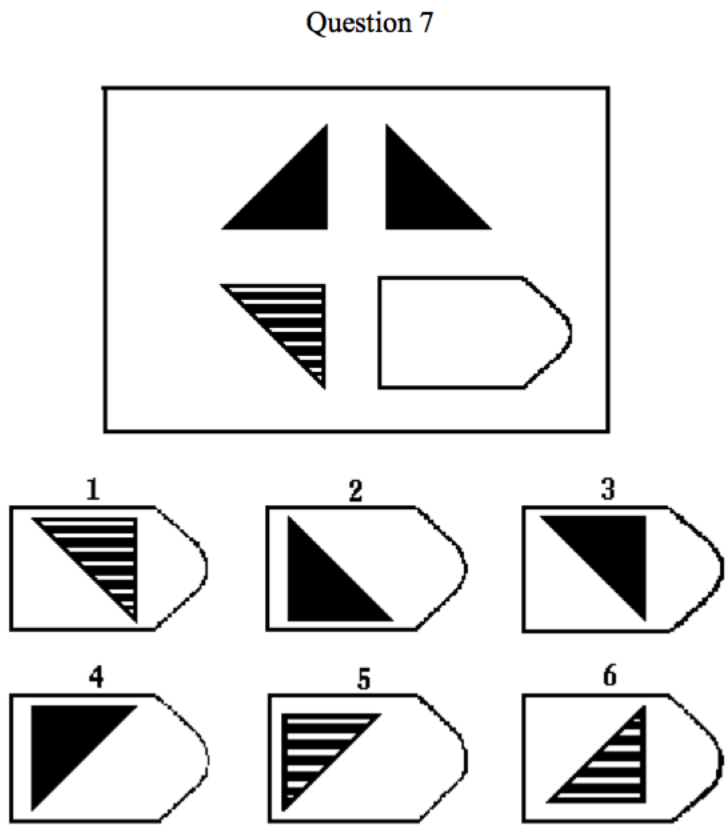



Figure 3.1: An Example of Logical Testing

The arithmetic test is only taken by the children, while the logical test is taken by both children and parents. The Cronbach's alphas for the arithmetic test and the logical test are respectively 0.88 and 0.85, suggesting a very high internal consistency, so we use the sum of the scores as the standard measurements for cognitive ability in this paper. Besides, the arithmetic test is incentivized with monetary reward for every right answer, while the logical test is not. After the interviewer computes the monetized reward for each twin in a pair, one is asked how much she will contribute to her twin sibling. This transfer is used as a measurement for altruism (Yi 2019).

**Subjective Well-being and Economic Preferences**

Defined as a combination of happiness, life satisfaction and positive affections (Diener 1984), subjective well-being is an important measurement about welfare. In LCCTS, the team uses a slightly modified subset of the Gallop World Poll (details seen in http://www.gallupworldpoll.com/content/24046/About.aspx). Yet, basic psychometric tests of this inventory find that the positive items and negative items are pretty independent, so we will use two factors "Positive Feelings" and "Negative Feelings" distinctively in the following part of the paper. The Cronbach's alpha within each factor is respectively 0.71 and 0.65.

The LCCTS also uses three self-report questions to measure risk and time preferences. The risk preference question is: "Y6. Which do you prefer? (1) Suppose there is a business, you can earn a profit of 10,000 yuan. (2) Suppose there is a business, the possibility that you can earn a profit of 20,000 yuan is 50%, and 50% you will earn nothing. (3) The above two make no difference to me." And the time preference questions are: "Y7. Suppose you can get 100 yuan tomorrow, or 120 yuan 8 days later, you would (1) get 100 yuan tomorrow (2) get 120 yuan 8 days later.", and "Y8. Suppose you can get 100 yuan 100 days later, or 120 yuan 108 days later, you would (1) get 100 yuan 100 days later (2) get 120 yuan 108 days later." Despite the fact that these questions are not incentivized, they may still reflect some aspect of risk and time preferences as they significantly correlate with revealed preferences (Wölbert and Riedl 2013).

### 3.2.3 Analytic Roadmap and Empirical Strategy

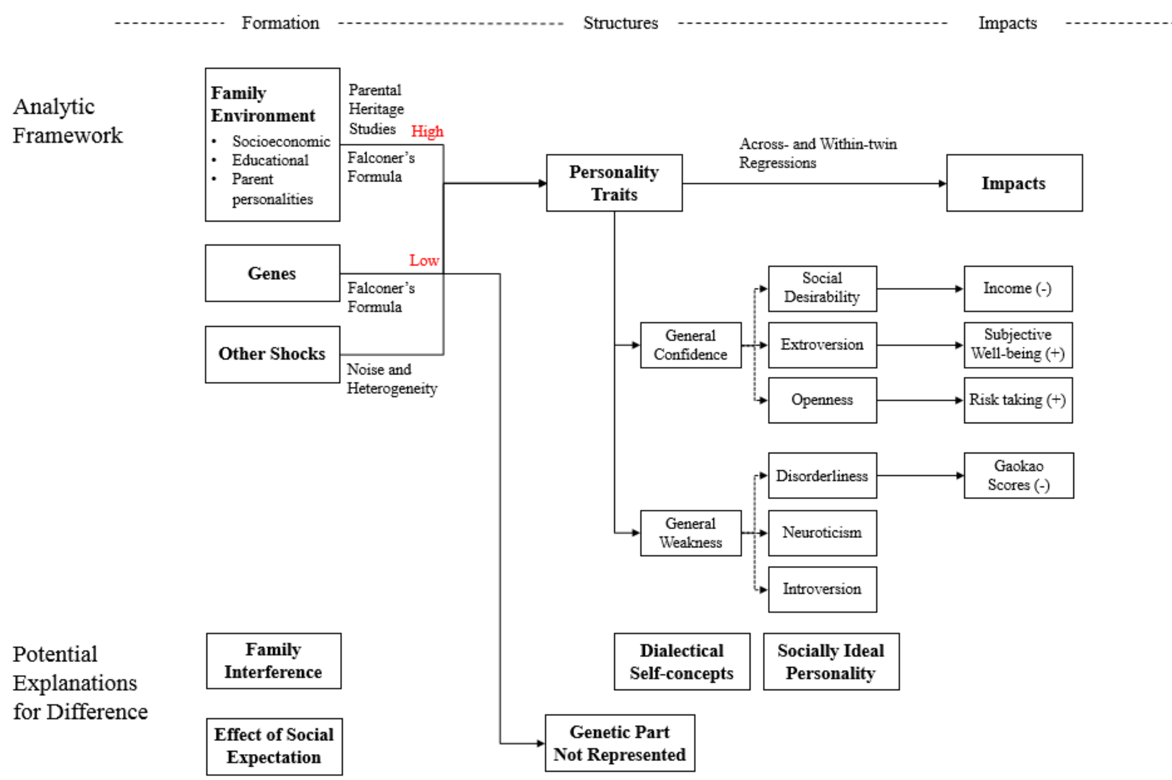



Figure 3.2: Roadmap of this Paper

Note: this roadmap summarizes the major concepts and their relationships within this paper.

**Personality Structure**

We follow the canonical psychometric techniques to test the property of the BFI-44 in China. We use Exploratory Factor Analysis with varimax rotation to detect the factor structure of the BFI-44 and test the reliability of our construction using standard measures such as Cronbach's alpha and split-half reliability tests.

**Personality Formation**

This part contains two categories of methodologies; in the first part, we use the standard twin study design to compute the heritability of personality traits in China; in the second part, we study the mechanism of personality formation by a within-twin regression design to study how different parental treatments may impact children's behaviors.

There are various models for standard twin design. Usually, we start with computing the intraclass correlations within monozygotic (MZ) twins and dizygotic (DZ) twins respectively.

In the prospectus we are mainly providing the results computed from the standard ACE model and heritability coefficients based on the Falconer's formula. In the appendix, we show robustness checks with different methods, and formally build a framework of genetic influence model of personality.

**Personality Impacts**

The empirical identification of causal effects of personality impacts is generally tricky. In previous studies, (Almlund et al. 2011; Borghans et al. 2008; Heckman et al. 2019), detailed discussion is made about potential identification problems if we just regress economic outcomes with personality. Potential problems may include:

(1) Omitted variable problems. In most correlational personality-outcome studies, researchers are just putting outcomes at the left hand side, and personality and other controls at the right hand side. These regressions may be problematic even with detailed structural setups, because there might be some unobserved heterogeneous attributes. For instance, they may reflect some certain family backgrounds, such as partisanship and local connections, which may instead be the fundamental attributes that determine economic performances.

(2) Reverse causality. This is crucial when we try to link personality and economic outcomes, such as income. Economic outcomes may influence people's subjective well-being and emotional status, and therefore impacting personality reports. Some literature chooses to avoid this problem with earlier measurements of traits instead of contemporaneous ones, yet this may magnify

another important problem: measurement error, because earlier measurements may be poor proxies of the current ones.

(3) Measurement error problems. The literature discussing measurement errors of personality and non-cognitive skills is huge. In this paper, we have to use the subjective reports of personality and well-being. However, we can assist our analysis by controlling the objectively measured items, such as arithmetic and logical abilities.

(4) Situationist view, as denoted in a previous meta-study (Mischel 2013). Mischel (and some economists) believe that there is nothing such as "Stable Personality Traits". Their view is that behaviors are usually just responses to certain scenarios, and is highly variable across situations. Indeed, in Asia this concern is even stronger because East Asian people care less about self-consistency (Kanagawa et al. 2001). We use a within-twin design model with a variety of techniques, trying to minimize the influence of endogeneity problems.

With twin studies, we can specifically look at within-twin difference to avoid omitted variable biases. This will cancel out the shared environmental effect, which is mainly family's socioeconomic backgrounds and most of the nurturing styles. If we look at the MZ twins, genetic differences are also canceled out. However, the unobserved heterogeneous nonshared environmental effect cannot be canceled out; it is difficult to capture all the shocks that the children have faced separately. To deal with this, we (1) need controls for observed heterogeneous characteristics that may be significant, such as grades, cognitive abilities, and other non-personality traits; and (2) may want information about their personality in their early age, although relevant measurements within this paper have many limitations.

Reversed causality problems are also not naturally mitigated by a within-twin design. However, one way to deal with this is to look at heterogeneous effects: we try to find stories about why for different groups of people (for instance, male and female), the coefficients may be very different because of certain socioeconomic reasons. If so, we can add evidence to say that reversed causality is not that severe because it is counter-intuitive that the influence of outcomes on personality report will vary hugely across groups.

For measurement error problems, standard psychometric tools come to mitigate this problem. As suggested in previous studies (Borghans et al. 2008), measurements for a lot of economic variables should be obtained from a psychometrically sound way. If the measurement has good psychometric properties, then we will be more confident to say that the measurement error problem is not crucially exacerbating our results.

## 3.3 Results

### 3.3.1 Personality Structure

Since the computation of genetic heritability values rely on proper construction of personality factors, we report the results of personality structures first.

#### Correlation Structure

Before doing a factor analysis, it is most intuitive to show the correlation structures of all 44 items.

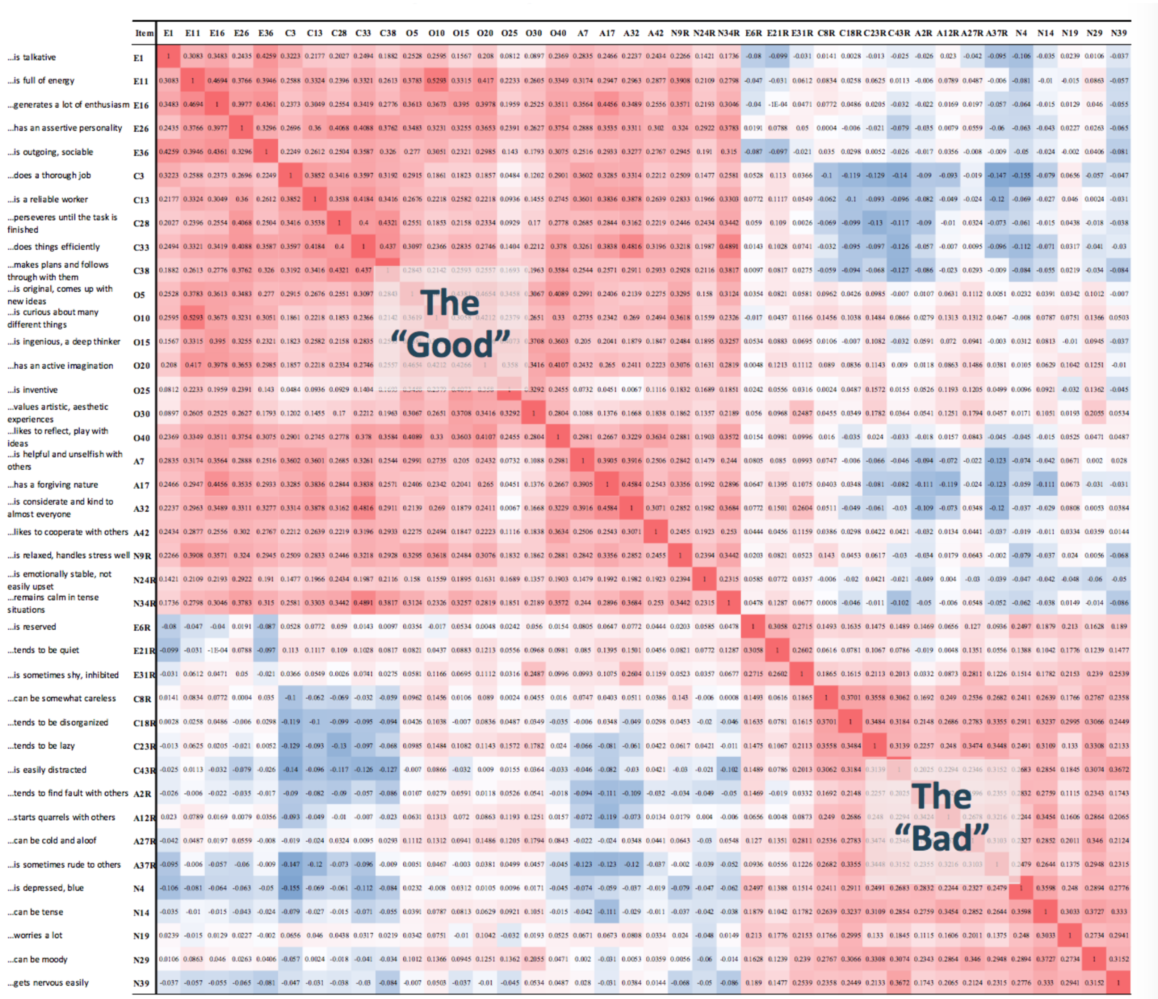



Figure 3.3: Correlation Structure of BFI-44 in China, N=3,977

This graph is a demonstration of the correlation structure of the 44-item Big Five Inventory in China. Correlations are Pearson.

This is a special correlation structure in the following senses:

(1) "The Good" and "The Bad" in the correlation matrix have distinctive patterns. "The Good" includes all regular items designed for measuring Openness (O), Conscientiousness (C), Extraversion (E), Agreeableness (A) and reversed items for Neuroticism (N). "The Bad", on the contrary, includes all reversed items for O, C, E and A, and regular items for N. The definition of

"Good" and "Bad" are consistent with the concept of social desirable traits and their opposite in the literature (Erdle and Rushton 2011; Laajaj et al. 2019; Peterson et al. 2006).

(2) The correlations are relatively large within the two clusters, and have relatively low absolute values across them.

(3) Even within a designed dimension of a Big Five Factor, the cross-correlations of regular and reversed items are close to *0*. This is a crucially different feature of our results from a typical Western BFI-44 sample. This feature leads to low Cronbach's alpha's for C, E, A and N if we follow the original Five-Factor setup.

All three features are quite distinctive from the well-known US-Spanish study of the same inventory John et al. 1991, in which we observed good accordance with the standard Big Five personality structure. This unique correlation structure motivates us to treat social desirable and undesirable traits independently. This is a #1 important feature of Chinese Personality Structures: people tend to be dialectical in self-perception about their advantage and disadvantages. They can comfortably evaluate them as both good and bad, or neither, which would "appear improbable, illogical, or even irrational in most Western nations" (Spencer-Rodgers et al. 2004, 2010b). This finding is also consistent with the finding in (Carciofo et al. 2016), in which they find that reversed items in BFI-44 tend to have bad psychometric properties. If we run a factor analysis (without any rotation) on the 44 items, we can easily detect that the first two factors are dominant, which respectively contain most of the "Good" and the "Bad" items. The eigenvalues for the first and second factors are 7.88 and 4.90, while the numbers drop significantly when it comes to the third one (2.26 for the whole sample). Also, we check for robustness in subsamples. For the children sample with N=1430, the values are 8.28 and 5.11, and the third one is 1.86. For the twins sample (N=970), they are 8.53, 5.15 and 1.8. This suggests that although there is inter-observation dependence among twin data, it does not lead to any difference of significance. All these suggest that the bifactoral structure is very robust., Also, in the third factors and after, there are almost no items with a factor loading >0.4. Such results are stable across many sub-samples (All sample, twins, and non-twins), justifying that the fundamental structure of our inventory is bi-factored.

Thus in the following parts of the paper, we will consistently treat them separately. These two factors are respectively denoted as "General Confidence (GC)" and "General Weakness (GW)".

| Item | Factor 1 | Factor 2 | Factor 3 | Factor 4 |
|---|---|---|---|---|
| E1 | 0.4499 | -0.1095 | -0.01 | 0.449 |
| E6R | 0.0755 | 0.3527 | 0.37 | -0.3457 |
| E11 | 0.637 | 0.0062 | -0.20 | 0.2603 |
| E16 | 0.648 | -0.0381 | -0.13 | 0.229 |
| E21R | 0.1677 | 0.2322 | 0.36 | -0.4856 |
| E26 | 0.6491 | -0.0704 | -0.03 | -0.0269 |
| E31R | 0.1833 | 0.4052 | 0.29 | -0.2871 |
| E36 | 0.566 | -0.0729 | -0.09 | 0.3669 |
| A2R | -0.0479 | 0.4586 | -0.14 | 0.0926 |
| A7 | 0.5441 | -0.0932 | 0.25 | 0.1229 |
| A12R | 0.0439 | 0.5208 | -0.16 | 0.1811 |
| A17 | 0.5713 | -0.1341 | 0.27 | 0.0771 |
| A22 | 0.2701 | 0.238 | 0.23 | -0.0323 |
| A27R | 0.1183 | 0.5535 | -0.03 | -0.0765 |
| A32 | 0.5909 | -0.0811 | 0.37 | 0.0088 |
| A37R | -0.0566 | 0.5649 | -0.08 | 0.1178 |
| A42 | 0.4977 | 0.009 | 0.12 | 0.1021 |
| C3 | 0.506 | -0.2154 | 0.26 | -0.0089 |
| C8R | 0.0812 | 0.5372 | 0.05 | 0.2646 |
| C13 | 0.5715 | -0.1516 | 0.25 | -0.0367 |
| C18R | 0.0164 | 0.6028 | 0.05 | 0.2539 |
| C23R | 0.0543 | 0.6208 | -0.16 | 0.027 |
| C28 | 0.5315 | -0.1506 | 0.19 | -0.1022 |
| C33 | 0.6498 | -0.164 | 0.18 | -0.0416 |
| C38 | 0.5676 | -0.1455 | 0.08 | -0.0955 |
| C43R | -0.0483 | 0.5857 | 0.08 | 0.1756 |
| O5 | 0.6102 | 0.0862 | -0.24 | -0.058 |
| O10 | 0.5659 | 0.1604 | -0.19 | 0.2186 |
| O15 | 0.559 | 0.0895 | -0.34 | -0.2399 |
| O20 | 0.6076 | 0.1386 | -0.29 | -0.0708 |
| O25 | 0.3664 | 0.154 | -0.49 | -0.2696 |
| O30 | 0.4529 | 0.2169 | -0.33 | -0.363 |
| O35R | 0.2398 | 0.1013 | 0.32 | -0.04 |
| O40 | 0.6224 | -0.0028 | -0.06 | -0.0676 |
| O41R | -0.1656 | 0.0867 | 0.37 | 0.2513 |
| O44 | 0.2748 | 0.295 | -0.33 | -0.298 |
| N4 | -0.0684 | 0.5577 | 0.11 | -0.0449 |
| N9R | 0.5698 | -0.0126 | -0.03 | 0.1298 |
| N14 | 0.008 | 0.6264 | 0.03 | 0.0224 |
| N19 | 0.0894 | 0.4283 | 0.35 | 0.0264 |
| N24R | 0.3805 | -0.0631 | 0.01 | -0.0528 |
| N29 | 0.1008 | 0.6254 | -0.03 | 0.0103 |
| N34R | 0.5941 | -0.0891 | 0.07 | -0.1391 |
| N39 | -0.0198 | 0.5373 | 0.28 | 0.0234 |

Table 3.2: Factor Structure for All Items (unrotated) in BFI-44 in China, N=3,977

### Factor Construction and Interpretation

Based on the dialectical self-concept and the correlations, we run exploratory factor analysis separately for the 26 social desirable items and the 18 undesirable items. [8] The factor analysis results with principle component method and varimax rotation are shown here respectively.

| Item | Description | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|---|
| **E1** | is talkative | 0.179 | **0.658** | -0.082 |
| **E11** | is full of energy | 0.171 | **0.665** | 0.262 |
| **E16** | generates a lot of enthusiasm | 0.252 | **0.622** | 0.223 |
| **E26** | has an assertive personality | **0.507** | 0.276 | 0.307 |
| **E36** | is outgoing, sociable | 0.299 | **0.580** | 0.091 |
| **C3** | does a thorough job | **0.548** | 0.301 | -0.061 |
| **C13** | is a reliable worker | **0.583** | 0.229 | 0.026 |
| **C28** | perseveres until the task is finished | **0.685** | 0.070 | 0.112 |
| **C33** | does things efficiently | **0.703** | 0.215 | 0.123 |
| **C38** | makes plans and follows through with them | **0.669** | 0.105 | 0.209 |
| **O5** | is original, comes up with new ideas | 0.255 | 0.427 | **0.483** |
| **O10** | is curious about many different things | 0.042 | **0.624** | 0.312 |
| **O15** | is ingenious, a deep thinker | 0.237 | 0.259 | **0.626** |
| **O20** | has an active imagination | 0.149 | 0.456 | **0.531** |
| **O25** | is inventive | 0.033 | 0.121 | **0.698** |
| **O30** | values artistic, aesthetic experiences | 0.131 | 0.065 | **0.660** |
| **O40** | likes to reflect, play with ideas | **0.417** | 0.336 | 0.365 |
| **O44** | is sophisticated in art, music, or literature | -0.001 | -0.065 | **0.631** |
| **A7** | is helpful and unselfish with others | 0.376 | **0.447** | -0.040 |
| **A17** | has a forgiving nature | **0.440** | 0.384 | -0.053 |
| **A22** | is generally trusting | 0.025 | 0.070 | 0.075 |
| **A32** | is considerate and kind to almost everyone | **0.552** | 0.297 | -0.055 |
| **A42** | likes to cooperate with others | **0.357** | 0.255 | 0.137 |
| **N9R** | is relaxed, handles stress well | 0.303 | **0.430** | 0.192 |
| **N24R** | is emotionally stable, not easily upset | 0.324 | 0.060 | 0.193 |
| **N34R** | remains calm in tense situations | **0.623** | 0.127 | 0.268 |

Table 3.3: Factor Structure for Desirable Items in BFI-44 in China, N=3,977

[8] The results generated from a pooled factor analysis can be retrieved in appendix. Generally things are similar, yet the predictive power of indicators generated this way is slightly weaker.

| Item | Description | Factor 1 | Factor 2 | Factor 3 |
|---|---|---|---|---|
| **E6R** | is reserved | -0.029 | 0.272 | **0.647** |
| **E21R** | tends to be quiet | 0.009 | -0.005 | **0.709** |
| **E31R** | .is sometimes shy, inhibited | 0.355 | -0.101 | **0.617** |
| **C8R** | can be somewhat careless | **0.619** | 0.121 | 0.072 |
| **C18R** | tends to be disorganized | **0.542** | 0.268 | 0.087 |
| **C23R** | tends to be lazy | **0.685** | 0.145 | 0.092 |
| **C43R** | is easily distracted | **0.537** | 0.162 | 0.093 |
| **O35R** | prefers work that is routine | 0.153 | -0.242 | **0.355** |
| **O41R** | has few artistic interests | -0.019 | 0.005 | -0.041 |
| **A2R** | tends to find fault with others | 0.143 | **0.704** | -0.074 |
| **A12R** | starts quarrels with others | 0.385 | **0.517** | -0.099 |
| **A27R** | can be cold and aloof | **0.581** | 0.175 | 0.205 |
| **A37R** | is sometimes rude to others | **0.623** | 0.192 | -0.047 |
| **N4** | is depressed, blue | 0.164 | **0.610** | 0.255 |
| **N14** | can be tense | 0.310 | **0.580** | 0.187 |
| **N19** | worries a lot | 0.120 | 0.317 | **0.440** |
| **N29** | can be moody | **0.482** | 0.363 | 0.227 |
| **N39** | get nervous easily | 0.303 | 0.279 | 0.308 |

Table 3.4: Factor Structure for Undesirable Items in BFI-44 in China, N=3,977

As is seen in the figures, we see three main factors in both categories, and the other factors only cover 1 or 2 items, such as trusting others or not in GC, and lacking of artist interests in GW. Dropping these singleton items, we get the $2 \times 3$ factor structure, briefly summarized by the following table:

This $2 \times 3$ structure has the following features:

(1) Chinese people seem to be orthogonal in regards of desirable and undesirable traits. Even within those traits with the "opposite" meanings, Chinese people do not necessarily give responses with negative correlations. For instance, in Extraversion and Introversion, their pairwise correlation is even slightly positive (though not significant).

(2) Within the desirable traits, E and O seem to resemble the E and O in Big 5; yet Social

| Dimension | Items | Tones | Items |
|---|---|---|---|
| Social Desirability | 11 | Desirable | E26,C3,C13,C28,C33,C38,O40,A17,A32,A42,N34R |
| Extraversion | 7 | Desirable | E1,E11,E16,E36,O10,A7,N9R |
| Openness | 6 | Desirable | O5,O15,O20,O25,O30,O44 |
| Disorderliness | 7 | Undesirable | C8R,C18R,C23R,C43R,A27R,A37R,N29 |
| Neuroticism/Hostility | 4 | Undesirable | A2R,A12R,N4,N14 |
| Introversion | 5 | Undesirable | E6R,E21R,E31R,O35R,N19 |
| Miscellaneous | 4 | // | A22, N24R, O41R, N39 |
| Total | 40 | // | // |

Table 3.5: Factor Structure of BFI-44 in China

Desirability is mainly a combination of Conscientiousness and Agreeableness in Big 5.

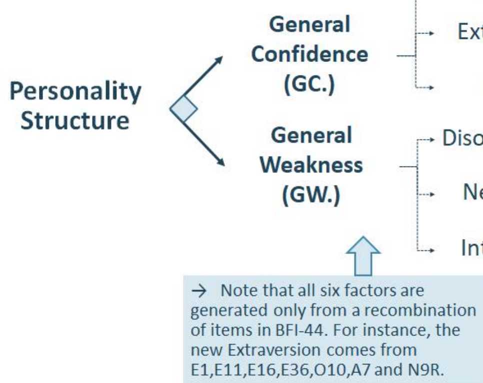
(3) Within the undesirable traits, Disorderliness is likely the "opposite" of social desirability.

(4) The Neuroticism/Hostility factor seems to be composed of some items of Neuroticism and some reversed items of Agreeableness. And specifically, if we look at the description of these items, they compose a tendency of being hostile and unfriendly with other people. This factor is an important negative trait in a society with high emphasis on interpersonal harmony.

(5) The Introversion factor is mainly composed of items that describe a tendency of being alone and stay with the status quo. It is therefore slightly narrower than the "Introversion" in Big Five.

**Reliability**

In this section, we use standard psychometric methods to justify our $2 \times 3$ factor structure and its superiority over directly taking the Big Five constructs.




| | S. | E. | O. | D. | N. | I. | GC. | GW. |
|---|---|---|---|---|---|---|---|---|
| Social Desirability | (0.85) | 0.677 | 0.463 | -0.094 | -0.123 | 0.224 | 0.896 | -0.026 |
| Extroversion | 0.677 | (0.79) | 0.501 | 0.062 | -0.037 | 0.070 | 0.854 | 0.023 |
| Openness | 0.463 | 0.501 | (0.76) | 0.208 | 0.151 | 0.154 | 0.732 | 0.174 |
| Disorderliness | -0.094 | 0.062 | 0.208 | (0.76) | 0.587 | 0.361 | 0.053 | 0.876 |
| Neuroticism | -0.123 | -0.037 | 0.151 | 0.587 | (0.64) | 0.279 | -0.020 | 0.758 |
| Introversion | 0.224 | 0.070 | 0.154 | 0.361 | 0.279 | (0.56) | 0.205 | 0.654 |
| GC. | 0.896 | 0.854 | 0.732 | 0.053 | -0.020 | 0.205 | (0.90) | 0.066 |
| GW. | -0.026 | 0.023 | 0.174 | 0.876 | 0.758 | 0.654 | 0.066 | (0.81) |

Figure 3.4: Reliability Test

Cronbach's alphas are shown in the parentheses. We can see that they are all arguably large. Even for Neuroticism and Introversion, as the items are relatively few. The cronbach's alphas are generally larger than what we have when simply applying the big five, as the following figure suggests:

| | E | C | O | A | N | GC | GW |
|---|---|---|---|---|---|---|---|
| **E** | **(0.559)** | 0.360 | 0.379 | 0.309 | -0.381 | 0.601 | -0.319 |
| **C** | 0.360 | **(0.708)** | 0.185 | 0.527 | -0.506 | 0.513 | -0.536 |
| **O** | 0.379 | 0.185 | **(0.751)** | 0.154 | -0.131 | 0.744 | 0.067 |
| **A** | 0.309 | 0.527 | 0.154 | **(0.589)** | -0.434 | 0.516 | -0.426 |
| **N** | -0.381 | -0.506 | -0.131 | -0.434 | **(0.612)** | -0.324 | 0.705 |
| **GC** | 0.601 | 0.513 | 0.744 | 0.516 | -0.324 | **(0.898)** | 0.066 |
| **GW** | -0.319 | -0.536 | 0.067 | -0.426 | 0.705 | 0.066 | **(0.810)** |

Note: Alphas are in parentheses.

The high correlation between C and A suggests that those two traits are inseperable in China.

Figure 3.5: Intercorrelations of GC, GW, and the Scores of Big 5 in Our Sample

Table 1
*Study 1: Psychometric Properties of the English and Spanish Big Five Inventory Scales*

| | | *α* | | *M* | | *SD* | | Correlations with indigenous Big Five scales[a] | |
|---|---|---|---|---|---|---|---|---|---|
| Scale | *n* | United States | Spain | United States | Spain | United States | Spain | *r* | Corrected *r* |
| Extraversion | 8 | .88 | .85 | 3.2 | 3.4 | .8 | .8 | .77 | .89 |
| Agreeableness | 9 | .79 | .66 | 3.8 | 3.8 | .6 | .5 | .60 | .83 |
| Conscientiousness | 9 | .82 | .77 | 3.6 | 3.5 | .7 | .7 | .63 | .79 |
| Neuroticism | 8 | .84 | .80 | 3.0 | 3.2 | .8 | .8 | .68 | .83 |
| Openness | 10 | .81 | .79 | 3.7 | 3.8 | .6 | .6 | .53 | .66 |
| *M* | 9 | .83 | .78 | 3.5 | 3.5 | .7 | .7 | .65 | .81 |

*Note.* *N* = 894 Spaniards and 711 Americans; *n* = number of items in the scale.
[a] Correlations in the Spanish sample only; correlations were corrected for attenuation due to unreliability using alpha.

Figure 3.6: Comparison-US/Spanish Cronbach's Alpha

Table 2

*Study 1: Intercorrelations Between the English and Between the Spanish Big Five Inventory Scales*

| Scale | E | A | C | N | O |
|---|---|---|---|---|---|
| Extraversion (E) | — | .17 | .09 | −.18 | .33 |
| Agreeableness (A) | .14 | — | .17 | −.23 | .16 |
| Conscientiousness (C) | .24 | .27 | — | −.20 | .17 |
| Neuroticism (N) | −.29 | −.31 | −.18 | — | −.14 |
| Openness (O) | .25 | .05 | .08 | −.14 | — |

*Note.* Correlations for the Spanish sample ($n = 894$) are above the diagonal; correlations for the U.S. sample ($n = 711$) are below the diagonal.

Figure 3.7: Comparison-US/Spanish Intercorrelations

However, as cited in Figure 3.5, 3.6 and 3.7, the Cronbach's alphas of the same inventory are much larger in the U.S. and Spain (Benet-Martinez and John 1998; John et al. 1991), and the cross-factor correlations are much smaller in the U.S. and Spain, as seen in the following table extracted from this paper. This further suggests that cultural factors may be a crucial factor that impacts the structures of personality, in accordance with our theories.

**Construction Validity**

Generally, using the new model generates better predict power for attitudes and behaviors than simply accepting the Five Factor model. For prediction of "positive" behaviors (abilities, positive feelings, etc), factors in the GC are much more significant, and for "negative" feelings, factors in GW are more significant instead. This implicates a "dual self" or dialectical self concept in various senses. Below is a table for a brief validity test of our construction and a comparison with the construction of FFM.

| | General Confidence | | | General Weakness | | | Big Five Traits | | | | | #Obs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | S | E | O | D | H | I | E | C | O | A | N | |
| Risk Preference | 0.054 | 0.073 | 0.133 | 0.121 | 0.055 | 0.042 | 0.032 | -0.045 | 0.138 | -0.011 | 0.021 | 3977 |
| Hyperbolic Discounting | 0.070 | 0.046 | 0.074 | 0.093 | 0.041 | 0.073 | 0.006 | -0.014 | 0.077 | -0.009 | 0.018 | 3977 |
| Delayed Gratification | 0.009 | -0.007 | 0.022 | -0.072 | -0.045 | -0.073 | 0.046 | 0.061 | 0.017 | 0.017 | -0.052 | 3977 |
| Math Test | 0.005 | 0.098 | 0.176 | 0.089 | 0.023 | -0.023 | 0.059 | -0.071 | 0.198 | -0.023 | -0.009 | 3977 |
| Logical Test | 0.057 | 0.114 | 0.215 | 0.004 | -0.033 | -0.017 | 0.091 | 0.014 | 0.226 | 0.040 | -0.066 | 3977 |
| Positive Feelings | 0.210 | 0.255 | 0.220 | 0.034 | -0.031 | 0.037 | 0.195 | 0.093 | 0.211 | 0.099 | -0.135 | 3753 |
| Negative Feelings | 0.012 | -0.014 | 0.054 | 0.203 | 0.188 | 0.173 | -0.084 | -0.105 | 0.041 | -0.094 | 0.209 | 3702 |
| Donation | 0.172 | 0.156 | 0.142 | 0.049 | -0.034 | 0.015 | 0.102 | 0.069 | 0.166 | 0.147 | -0.080 | 1114 |

Figure 3.8: Validity of Construction and Comparison with Using the FFM

The Pearson correlations that are larger than 0.09 are statistically significant. The validity tests show that for many dimensions of preferences or behaviors, using the 3+3 model has a better predictive power than using the Big Five. In risk preference, for example, openness and disorderliness in our model have a correlation of 0.133 and 0.121 (both significant), while openness in the Big Five has a correlation of 0.138 while others has very low significance. This indicates that if we use the 3+3 model instead of the Big Five, we would find a new dimension of personality which has almost the same predictive power compared to the known openness for risk preference. Similar things also take place for hyperbolic discounting, math tests and logical tests. Also, another keynote finding is that for behaviors that are aligned with positive social judgments (such as positive feelings and donation), dimensions in GC are predictive but dimensions in GW are not, and vice versa (such as negative feelings). This adds crucial evidence about the dialectical structure of personality in China. In China, people tend to treat words in a positive tone and a negative tone as two orthogonal dimensions, which sets up the foundation of personality assessments.

We add supporting evidence by comparing the predictive power of our 3 + 3 model with the traditional FFM model by comparing the adjusted R-square[9] in terms of prediction. We can see that our model generally increases the adjusted R-square by 20-30% for behaviors with a fixed, positive or negative tone, and keeps almost the same for behaviors without such. Mostly, this is a significant improvement than just using the FFM. The predictive power is comparable to the Western findings (R-square usually below 0.1, Ross and Nisbett 2011).

| Item Fit (Adjust R2) | 3*2 Model | FFM |
|---|---|---|
| Life Satisfaction | 0.066 | 0.054 |
| Positive Feelings | 0.079 | 0.064 |
| Negative Feelings | 0.059 | 0.048 |
| Logical Test | 0.054 | 0.055 |
| Maths Test | 0.450 | 0.310 |
| Risk Preference | 0.026 | 0.023 |
| Hyperbolic Discounting | 0.015 | 0.006 |
| Donation Behavior | 0.061 | 0.051 |

Table 3.6: Comparison of the adjusted R-square of the Dialectical model and FFM on behavioral tendences

Nevertheless, the correlations in the table above do not fully capture the relationships between personality and behaviors since there are non-linear effects. Thus, introducing data-driven clustering methods improves the prediction. For instance, “Traditionalists” is associated with strong risk aversion.

[9] adjusted for the fact that our model has one extra parameter.

**Typing Chinese People: a Cluster Analysis and Validity Checks**

In the reliability and validity checks above, we are mainly looking at linear relationships. To better justify the implications of newly constructed personality indicators, we can use an alternative method: cluster analysis. The idea of clustering is based on Gerlach et al. 2018, which uses a data-driven clustering to find that in general (of course, most data are drawn from Western samples), people can be classified into five categories, each of which has important real-world implications.

The current progress is a typical K-means clustering method and we find five important types. Their features are summarized in the following tables. If we increase the number of clusters, we still find that the five types systematically exist. Also, this classification is very predictable about certain cognitive, economic preference factors and economic well-being. This justifies the validity of this classification methodology, implying that in China, the clustering of personality may also deviate highly from that in the West.

These types are named according to the values of personality traits and related real-word behavioral tendencies:

(1) The Entrepreneur reports high in both GC and GW terms. They seem to be confident in their desirable traits, but they also report relatively high in undesirable traits, showing a highly dialectical self-concept. An Entrepreneur has the highest level of risk preference and hyperbolic discounting, showing a tendency of being aggressive and risky. They account for 15-20% of the whole whole population.

(2) The Traditionalist reports medium scores in GC terms (with SD/E above average and O below average), and very low in GW terms. These people seem to stick to traditions and a stable lifestyle, justified by the lowest tendency to take risks and a relatively low tendency to show present bias. They account for about 25-30% of the whole population.

(3) The Role Models resembles the same type in the larger-scale Western study (Gerlach et al. 2018), showing high in all GC and low in all GW terms. Their personality is mostly single-factored and show less dialectical self concepts. They have the best logical abilities and

highest subjective well-being. They account for about 10% of the whole population.

(4) The Silent Feeler reports low in GC terms but medium in GW terms. They seem to have the lowest openness to experience and stay in their comfort zones. The key behavioral patterns are low cognitive ability, low risk attitudes and low subjective well-being. They account for slightly more than 10% of the whole population.

(5) The Golden Mean ("Zhongyong") type reports around "Neutral" in most items, thus leading to a very low variance in their responses. Also, their behavioral patterns (even in objective tests) tend to stay in the middle. This means for this group, scores in personality may be less predictive about behaviors than other for. They account for about 1/3 of the whole population.

| | | Personality Types | | | | |
|---|---|---|---|---|---|---|
| | | The Entrepreneur | The Traditionalist | The Role Model | The Silent Feeler | The Golden Mean |
| ITEMS(Mean) | Whole | Group A | Group B | Group C | Group D | Group E |
| Social Desirability | **3.44** | 3.87 | 3.55 | 4.30 | 2.88 | 3.14 |
| Extraversion (in GC) | **3.40** | 3.91 | 3.48 | 4.17 | 2.73 | 3.14 |
| Openness (in GC) | **2.84** | 3.31 | 2.66 | 3.60 | 1.94 | 2.87 |
| Disorderliness | **2.61** | 3.24 | 2.06 | 2.17 | 2.31 | 2.94 |
| Hostility | **2.39** | 2.85 | 1.87 | 1.89 | 2.18 | 2.73 |
| Introversion | **3.03** | 3.46 | 2.77 | 2.93 | 2.84 | 3.10 |
| Basic Arithmetic Ability | **1.44** | 1.83 | 1.35 | 1.52 | 0.83 | 1.53 |
| Logical Inference Score | **9.45** | 9.67 | 9.58 | 9.94 | 8.13 | 9.62 |
| Risk Attitudes | **0.73** | 0.89 | 0.53 | 0.85 | 0.62 | 0.80 |
| Hyperbolic Discounting | **24%** | 30% | 20% | 25% | 16% | 26% |
| General Confidence | **3.27** | 3,72 | 3.29 | 4.04 | 2.62 | 3.08 |
| General Weakness | **2.70** | 3.19 | 2.28 | 2.32 | 2.50 | 2.94 |
| Openness (in Big 5) | **2.95** | 3.32 | 2.83 | 3.62 | 2.25 | 2.93 |
| Conscientiousness (in Big 5) | **3.43** | 3.37 | 3.75 | 4.13 | 3.25 | 3.10 |
| Extraversion (in Big 5) | **3.25** | 3.41 | 3.43 | 3.79 | 2.87 | 3.04 |
| Agreeableness (in Big 5) | **3.49** | 3.52 | 3.73 | 4.02 | 3.37 | 3.20 |
| Neuroticism (in Big 5) | **2.66** | 2.90 | 2.30 | 2.07 | 2.76 | 2.90 |
| Variance in GC Items | **0.79** | 0.89 | 0.85 | 0.88 | 0.88 | 0.63 |
| Variance in GW Items | **0.86** | 1.00 | 0.91 | 1.08 | 0.92 | 0.68 |
| Variance in all items | **0.91** | 0.99 | 1.02 | 1.31 | 0.91 | 0.67 |
| Observations | 3977 | 631 | 919 | 438 | 547 | 1442 |

Note: Numbers in red/blue are those higher/lower than the whole level.

Table 3.7: Personality Classification and Other Traits, N=3,977

| ITEMS(Mean) | Whole | Entrepreneur | Traditionalist | Role Model | Silent Feeler | Golden Mean |
|---|---|---|---|---|---|---|
| Life Satisfaction | **5.72** | 5.87 | 5.87 | 6.43 | 5.06 | 5.59 |
| Feeling happy | **85%** | 90% | 87% | 93% | 71% | 86% |
| Feeling Satisfied | **59%** | 64% | 57% | 75% | 43% | 58% |
| Feeling Angry | **13%** | 19% | 6% | 9% | 11% | 17% |
| Feeling Sad | **11%** | 17% | 4% | 7% | 10% | 13% |
| Feeling Stressed | **49%** | 57% | 41% | 52% | 44% | 52% |
| Feeling Worried | **43%** | 51% | 36% | 33% | 42% | 47% |
| Observations | 3683 | 570 | 873 | 400 | 507 | 1333 |

Note: Sample size is smaller because some people missed some items.

Table 3.8: Personality Classification and Subjective Well-being, N=3,977

### 3.3.2 Personality Formation

This part contains three subsections. The first subsection uses the ACE model and the Falconer's formula to document that in China, genetic heritability of personality traits is relatively low, and the shared and non-shared environmental effects are both very high. The second subsection shows that in China, couples resemble each other much more than the Western findings, and parents resemble children less but still more than the Western findings. The third subsection shows effort in causal analysis of how parental interventions influence personality. We find suggestive evidence that intervention under parent-child discrepancies may have permanent effect on personality development.

**Computing Heritability from Twin Study**

The baseline message of this part is about low heritability of personality traits in China. In the following table, heritability is measured by the difference of intercorrelation coefficients of monozygotic and dizygotic twins.

| Item | MZ (Corr %) | DZ (Corr %) | Heritability |
|---|---|---|---|
| Social Desirability | 44 | 60 | -0.32 |
| Extroversion (in 6) | 53 | 42 | 0.22 |
| Openness(in 6) | 58 | 54 | 0.08 |
| Disorderliness | 64 | 60 | 0.08 |
| Hostility/Neuroticism | 58 | 61 | -0.06 |
| Introversion | 52 | 36 | 0.32 |
| General Confidence | 54 | 62 | -0.16 |
| General Weakness | 69 | 63 | 0.12 |
| Positive Feelings | 61 | 56 | 0.10 |
| Negative Feelings | 59 | 54 | 0.10 |
| Risk Preference | 47 | 30 | 0.34 |
| Participation in Gaokao | 84 | 60 | 0.48 |

Table 3.9: Genetic Heritability of Personality Traits

| Item | Within-Parent | Father-Child | Mother-Child |
|---|---|---|---|
| Social Desirability | 0.48 | 0.35 | 0.33 |
| Extroversion (in 6) | 0.43 | 0.20 | 0.18 |
| Openness(in 6) | 0.52 | 0.26 | 0.33 |
| Disorderliness | 0.50 | 0.44 | 0.38 |
| Hostility/Neuroticism | 0.43 | 0.33 | 0.31 |
| Introversion | 0.33 | 0.19 | 0.17 |
| Positive Feelings | 0.68 | 0.47 | 0.47 |
| Negative Feelings | 0.59 | 0.36 | 0.38 |
| Logical Ability | 0.67 | 0.51 | 0.43 |
| Risk Preference | 0.34 | 0.32 | 0.24 |

Table 3.10: Personality Similarities Within Families

### Within-family Similarities

To study the robustness of the findings above, we test the correlation structures of personality traits and other cognitive/non-cognitive skills within a family. In general, we find that the similarities are larger than the findings in the West (Glicksohn and Golan 2001; Little et al. 2006; Troll et al. 1969). Specifically, the intraclass correlation within couples is surprisingly high, comparable to that of monozygotic twins. This suggests a strong tendency of either assortative matching before marriage or a large convergent effect after marriage. Unfortunately, due to the lack of pre-marriage personality data, it is hard to test which is the key mechanism.

**Further Evidence on Personality Formation**

In this part we focus on studying how family intervention impacts personality. Despite the importance of this part, the causal identification is subject to various challenges according to the discussions above. The major reason is that if we look at within-twin differences, we have to rely on the assumptions that the "shared environmental effect" is no longer fully shared. In other words, when family education turns to the nonshared effect, things get complicated. Another challenge is that the difference in treatments is actually a *consequence* of their personality differences. This reverse causality problem is nonneglible. One way to deal with this is linking the temperament reports made by a parent in the 2002 wave of this sample as a proxy of the earlier personality of the children. Unfortunately, the within-twin variance is extremely low for MZ twins. Further versions of this paper will try to deal with these problem formally.

Another way is to look at events that may be more "random". One thought is to only consider the education style when the children have conflicts or discrepancies with parents because this may not happen extremely often. However, this setup is still open to question because if the conflicts happen more than a few times, the different will cancel out due to Law of Large Numbers.

Our findings are also linked to the literature of situationist social psychology (Aronson 2003; Ross and Nisbett 2011), which argues that most behaviors should be predicted by situations but not inherent traits. In this paper, our findings show mixed evidence for China. On the one hand, as a collectivist, interdependent society, China expects to see larger effect of situation than personality on human behaviors. This is reflected in the dialectical structures of personality, which implies that different situations would trigger different personality-trait-like tendencies which might have the opposite meaning. However, there are still some "stable traits" if we relax the concept of self a bit. Allowing a self with both "Yin" and "Yang" sides, we would see that "Yin" and "Yang" traits still have considerable predictive power of personality traits within the relevant domain. For instance, if we want to predict donation (a "Yang" trait since it is positive), we should only rely on the positive dimensions of personality, but not those negative ones. They are in orthogonal domains.

### 3.3.3 Personality Outcomes

**Baseline Results**

In this part, we use a within-twin difference method to study how personality impacts economic preferences and outcomes. This allows us to cancel out shared unobserved heterogeneity effects. The basic results, gaokao (college entrance exams score), 12-month average income, measured risk attitudes and subjective well-being are presented here.

| | (1) Gaokao Score | | (2) Income | | (3) Risk Attitude | | (4) Subjective Wellbeing | |
|---|---|---|---|---|---|---|---|---|
| | Across | Within | Across | Within | Across | Within | Across | Within |
| Age | 3.54*** | | 0.05*** | | 0.00 | | 0.03* | |
| | (2.73) | | (3.81) | | (-0.21) | | (1.81) | |
| Social Desirability | -9.42 | -18.3 | -0.45** | -0.60** | 0.02 | -0.20* | 0.21 | 0.02 |
| | (-0.72) | (-1.30) | (-2.31) | (-2.18) | (0.19) | (-1.76) | (1.06) | (0.11) |
| Extroversion | 1.91 | 14.8 | 0.18 | 0.08 | -0.07 | -0.05 | 0.51*** | 0.53** |
| | (0.16) | (1.11) | (0.90) | (0.37) | (-0.82) | (-0.50) | (2.72) | (2.50) |
| Openness | 5.85 | -1.38 | 0.20* | 0.26 | 0.19*** | 0.35*** | 0.17 | -0.08 |
| | (0.59) | (-0.12) | (1.65) | (1.46) | (2.98) | (3.93) | (1.00) | (-0.45) |
| Disorderliness | -22.51** | -25.93** | -0.06 | -0.26 | 0.14** | 0.02 | -0.05 | -0.23 |
| | (-2.28) | (-2.18) | (-0.51) | (-1.18) | (1.99) | (0.17) | (-0.36) | (-1.13) |
| Hostility | 9.16 | 21.41* | -0.11 | 0.08 | -0.05 | -0.07 | -0.19 | -0.22 |
| | (1.08) | (1.77) | (-0.95) | (0.36) | (-0.79) | (-0.89) | (-1.41) | (-1.27) |
| Introversion | 12.67 | 22.45** | -0.11 | -0.24 | -0.16*** | -0.12 | 0.07 | 0.02 |
| | (1.24) | (2.23) | (-0.84) | (-1.44) | (-2.60) | (-1.57) | (0.40) | (0.11) |
| _cons | 7495.77*** | 421.02*** | 111.92*** | 12.12*** | -2.76 | 1.11** | 69.24* | 5.08*** |
| | (2.92) | (7.39) | (4.22) | (14.02) | (-0.17) | (2.58) | (1.90) | (5.74) |
| N | 229 | 249 | 222 | 263 | 802 | 900 | 752 | 850 |
| R2 | | 0.12 | | 0.13 | | 0.04 | | 0.03 |

t stats in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Table 3.11: Personality and Economic Outcomes

Among the results above [10], we can see that most results are consistent with our prediction and the current literature, while the most surprising result is that Social Desirability seems to negatively affect income. As is discussed above, SD is definitely an indicator that makes people better fit in the Chinese society, and most literature suggests that such properties will lead to more successful economic outcomes. Yet as a combination of Conscientiousness, Agreeableness and

[10] The "Across" regressions are random effect models, and the "Within" regressions have family fixed effects.

(somewhat) Emotional Stability, Social Desirability is expected to have mixed economic impacts based on the Western literature, because Conscientiousness is generally associated with better financial outcomes, while Agreeableness is the opposite. Thus, there may be mixed mechanisms about this negative relationship, and we need to look into it further.

### Heterogeneous Effects and Further Insights

To study the mechanism of the "horse races" for Social Desirability, we separate the children into two categories based on their family income in 2002. Since we are mainly looking into within-twin differences, this standard does not lead to a self-selection problem. Here is a table in which we look at different regression coefficients within twins coming from richer and poorer families, and of different genders.

Sexual heterogeneity effects is also an interesting point to look at. In the Western countries, it is generally found that males with higher agreeableness tend to have worse financial outcomes, and this effect is very thin for females (Judge et al. 2012; Matz and Gladstone 2018), because "agreeable men disconform (and disagreeable men confirm) conventional gender roles, agreeableness was expected to be more negatively related to income for men (i.e., the pay gap between agreeable men and agreeable women would be smaller than the gap between disagreeable men and disagreeable women)". However, if we put the same logic in China, things may get reversed: agreeable (high SD) women confirm conventional the gender role in China – which is not encouraged to work hard outside at all, but stay at home and take care of the family. As the saying goes, “Men are breadwinners; women are homemakers.”, women conforming to the gender role may result in the opposite income impact in China, and we study this hypothesis in this paper.

These sexually asymmetric heterogeneous effects sign that the major channel about our integrative regression may come from female career participation. This result is interesting because it shares very similar channel (social conformation) with the Western findings, but leads to the opposite outcomes. Also, it is valuable to mention that this finding can largely mitigate the potential reverse causality problem. The logic is: if the personality is reported because of income difference

| | (1) Backgrounds | | (2) Gender | | (3) Male | | (4) Female | |
|---|---|---|---|---|---|---|---|---|
| | Poorer | Richer | Male | Female | RB | PB | RB | PB |
| Social Desirability | -1.61*** | -0.16 | -0.58* | -0.13 | -1.00* | -0.07 | -3.55** | 0.47 |
| | (-3.62) | (-0.43) | (-1.86) | (-0.22) | (-2.09) | (-0.16) | (-3.02) | (0.64) |
| Extroversion | 0.87** | -0.19 | 0.04 | -0.02 | 0.41 | 0.1 | 1.26** | -0.97 |
| | (2.53) | (-0.67) | (0.16) | (-0.05) | (1.01) | (0.31) | (2.89) | (-1.24) |
| Openness | 0.33 | 0.24 | 0.14 | 0.51 | -0.02 | 0.03 | 1.34** | 0.64 |
| | (1.33) | (0.86) | (0.64) | (1.34) | (-0.06) | (0.09) | (2.40) | (1.16) |
| Disorderliness | -0.45 | -0.21 | -0.03 | -0.74* | -0.02 | -0.02 | -0.76 | -0.79 |
| | (-1.48) | (-0.71) | (-0.12) | (-1.71) | (-0.06) | (-0.06) | (-1.49) | (-1.31) |
| Neuroticism | -0.16 | 0.33 | 0.39 | -0.47 | 0.32 | 0.56 | -1.56*** | 0.01 |
| | (-0.54) | (0.97) | (1.45) | (-1.07) | (1.00) | (1.45) | (-3.61) | (0.02) |
| Introversion | -0.02 | -0.25 | -0.40* | -0.28 | -0.73** | -0.2 | 1.07** | -0.42 |
| | (-0.07) | (-1.03) | (-1.80) | (-0.94) | (-2.37) | (-0.63) | (2.83) | (-0.76) |
| _cons | 13.36*** | 10.75*** | 11.70*** | 12.80*** | 13.46*** | 8.99*** | 16.88*** | 12.83*** |
| | (13.93) | (7.70) | (11.42) | (8.49) | (14.61) | (5.08) | (8.00) | (5.08) |
| N | 110 | 153 | 138 | 125 | 56 | 82 | 54 | 71 |
| R2 | 0.46 | 0.06 | 0.19 | 0.19 | 0.74 | 0.09 | 0.71 | 0.25 |

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Table 3.12: Personality and Income: Heterogeneous Effects

or shocks, this effect is very unlikely to show the above mentioned patterns across the four groups we look at; it does not make a lot of sense to say that only women who came from richer families are influenced by this channel; nor they seem to report *lower*, but not higher, social desirability when they have a good mood resulted from higher income. Also, the complementary assortative matching (a socially desirable woman matches an undesirable man who earns more money) is also unlikely to be true, because we have observed extremely strong evidence for similarity-based assortative matching within their parents.

## 3.4 Discussion

In this part, we specifically link the surprising results from Western observations to the current literature in economics and psychology. We explain why these results are not as surprising as the first impression.

### 3.4.1 Personality Structures

We detect a personality structure that resembles the Big Five but has two important differences; (1) We need to treat desirable (GC) and undesirable (GW) traits independently; (2) Within the desirable traits, which are measured with a higher reliability, it is hard to distinguish agreeableness, conscientiousness and emotional stability, which altogether generate a China-specific factor, Social Desirability, or "Ren". This finding, in other words, depict a "Yin-Yang" structure on the relationship between personality and contexts: for Chinese people, there are two types of contexts: positive and negative. Across these two contexts, traits seem to be not stable; but when the context is fixed (Yin, or negative; and Yang, or positive), stable traits do exist and their predictive power of behaviors or preferences is comparable to that in the West. In fact, there exist rich cultural psychology and personality studies literature supporting this results.

The GC-GW structure is a typical and a bit extreme case of flexible and dialectical self-concept.

The inseparability of agreeableness, conscientiousness and emotional stability mainly comes from social expectation. The ideal personality image of ancient China is likely to have a permanent effect. As is mentioned above, most part of personality in China comes from nurture, and the child can determine to conform to or go against the Confucian education. Those people who are inclined or educated to conform with the society will show both Conscientiousness and Agreeableness, and vice versa. However, it leads to an inconsistency if one shows high Conscientiousness but low Agreeableness, or the opposite. This is supported by simply looking at the correlation of Conscientiousness and Agreeableness in China. In our paper, if we assume that the FFM is *suitable*, this correlation will be 0.52; in Carciofo et al. 2016, this correlation is 0.37; while in the most cited study using this inventory in the West (Benet-Martinez and John 1998), this correlation are 0.27 and 0.17 respectively within Spanish and American samples. In other countries, literature also shows that this number is usually smaller in Western countries and larger in East Asian countries (Denissen et al. 2008; Namikawa et al. 2012; Plaisant et al. 2010; Yoon et al. 2002). This adds further evidence on the correlation of C as A special cultural feature, and in China, this relationship is extreme.

Furthermore, the literature of GFP (General Personality Factor) (Musek 2007) also gives support to the validity of our finding. Specifically, some researchers believe that there is an alpha-beta structure within personality: the former includes E and O, and the latter includes C, A and N (Rushton and Irwing 2008; Van der Linden et al. 2010). To some extent, our results within the GC range fits well in this literature; and it is likely that the cultural cultivation has strengthened the unity of C, A and Emotional Stability as a whole factor.

Nevertheless, the discussions above may still be subject to questions because the discussion above is mainly based on the positive side: our construction of E, O and SD only include positive items, and the structures within the negative side is not exactly symmetric. However, because the BFI-44 *does not* have enough number of reversed items for Extraversion and Openness, it is less confident for us to establish the inner structure of GW than that of GC in this paper. Yet, the fact that the constructed within-GW factors still has good predictive powers in certain behaviors still necessitates the inclusion of these indicators in a Chinese personality model.

### 3.4.2 Personality Formation

The major finding in our paper can be summarized in two sentences; (1) In China, the genetic heritability of personality traits are much lower than that in Western countries and Japan, and the family education (shared environment effect) plays a significantly larger role. (2) In China, the major channel through which family education influences personality is how parents treat Children when they have discrepancies or conflicts. These results have their positions in the literature about behavioral genetics and development psychology.

Typically, we observe a genetic heritability between 0.4-0.6 for personality traits measured with Big Five. Why China is so different? One possible piece of evidence is the relatively authoritative ("strict and warm") and authoritarian ("strict and cold") parenting style in China, especially in areas which are far from the more liberal, coastal provinces (Chao 1994; Chen et al. 1997; Xu et al. 2005). These two types of parenting styles are very different from the permissive style prevalent in the West. The typical difference of an Eastern parenting style (Authoritarian and Authoritative) is that parents have strict rules about children's behaviors out of their expectation. In the final version we will make a systematic review on the studies of parenting styles and personality outcomes. Also we will test this story within our data.

Another interesting coherence with the current literature hides in (Polderman et al. 2015). Although this paper suggests that most behaviors are seriously genetic heritable, there are two traits for which the MZ and DZ correlations are very close: social interaction ($r_{MZ} = 0.34,\ r_{DZ} = 0.27$); and social values ($r_{MZ} = 0.49,\ r_{DZ} = 0.41$). This coincides our finding of an extremely low heritability (even negative) for behaviors that relate to social norm, but a relatively considerable heritability for Introversion/Extraversion. As we discussed above, a large part of personality is rather social than individual. These results together may give more support of our findings in this paper.

### 3.4.3 Personality Outcomes

In this part, we have found robust relationships between personality indicators and economic outcomes, and it is very likely that these relationships are causal. The most interesting question remains here: why Social Desirability is a negative trait for income? Summarizing our results, the current literature and the socioeconomic backgrounds of Yunnan province in China, we have the following discussions:

(1) How social desirability may impact income is a horse race. On the one hand, higher SD means higher conscientiousness, and therefore better grit to stick to goals and work efficiently;

also, higher SD means a better fit in the society, leading to a potentially better social capital and better income. On the other hand, higher SD also means less tendency to take risks and be aggressive, and less tendency to refuse unreasonable requests and bargain for their wage actively. A too high agreeableness/SD may be the "curse of loveliness", and this is observed in our data, especially for women.

(2) The gender gap may come from the social norms and social stereotypes about women. In traditional Confucian values, women are encouraged to be family-oriented and inactive in pursuing their own careers. In Yunnan province, a rather underdeveloped region in early 21st Century, such values are strong for the Han-ethnic groups there. The women who have a higher SD may likely to stick to traditional social roles and do not pursue an active career path. On the contrary, Extraversion contributes to a higher income, indicating that "going out" is really important for improving the income status.

(3) There are two important limitations about the effect we detect. First, what we detect is a temporary income. The children are rather young at the survey time (<30 years old), and we cannot arbitrarily refuse that people with higher SD may have a lifespan potential of higher income. This channel can be partially studied by looking at the career choice of different people. Second, the higher SD for women may help them perform better in marriage markets. They may be more caring and tender, thus making them better spouses and able to attract a partner with higher income. There is suggestive evidence in this paper that this mechanism is not likely to be true, but it is relatively challenging to use the limited data to do so.

(4) Another important challenge on this topic is that it is always an interaction of personality tendencies and the specific social context an individual is embedded. Thus even if we can use within-twin design, the personality traits and their growth environments (the "A" and "CE") are not separable during the formation processes. For instance, parents may treat them differently because they show some differences in their personality, while this difference in treatment may also in turn impact their future personality formation. In this paper, the fact that in 2002 the parents tend to think of the two identical twins as having the same personality weakens such impact, but it might

still work out in the outside environment. Thus, the real impacts are not fully identifiable.

## 3.5 Conclusion

### 3.5.1 Some Words to Future Related Studies

We expect that this paper will proceed a number of personality studies in China, and will provide some new insights about psychologists and economists.

*To Psychologists:*

(1) We need to localize psychometric tools in China, especially those with reversed items. As previous work (Peng and Nisbett 1999; Sims et al. 2015; Spencer-Rodgers et al. 2004, 2010b) and our research suggest, the dialectical thinking problem is a common phenomenon in measuring emotions, preferences and personality in China. Future research that includes inventories with reversed terms are therefore encouraged to replace the reversed items into regular ones, in case they would have to drop these items because keeping them leads to a bad internal consistency and difficulty in explaining the results.

(2) We need to carefully review the currently popular view of "Parents, but not parenting matter" in the developing world, especially countries with an interdependent thinking style. In an interdependent culture, as recent cross-cultural researches (Choi et al. 2007; Kitayama and Uchida 2005; Markus and Kitayama 1991; Nisbett et al. 2001) and many other studies suggest, personality and the self image is a highly socially dependent thing. This, plus the similarly low genetic heritability of social interactions and values in Polderman et al. 2015 may lead to warnings about looking at the "nature vs nurture" problem in the non-WEIRD world. Cross-cultural awareness and studies should be introduced in behavioral genetics studies.

(3) We call for further study of the cultural and historical backgrounds of cognitive style formation. Like the rice theory and the pathogen theory, we need more systematic studies that may fit in a larger scale of world. It will be also valuable to do such twin studies in other parts of China, especially those provinces in the North, which may generate results more resembling the West

because it is believed that Northern China has less holistic thinking than Southern China.

*To Economists:*

(1) We call for future intervention studies in China to further study the differences about personality in China. Despite the novel findings, our paper, even using twin data, is still potentially influenced by endogeneity problems. And as mentioned in previous research (Almlund et al. 2011; Heckman et al. 2019), the safest way of studying a causal relationship between personality and economic outcomes is to design random controlled trials, or intervention studies.

(2) The definition and application of personality skills may need to be considered from a cross-cultural perspective. Some personality traits (such as agreeableness) are skills in one cultural setup, but burdens in others. This implies that training programs focusing on certain skills should be adjusted to fit better in target cultures.

(3) In future surveys for economic research purposes, it may be marginally inexpensive but really useful to add personality assessments and pair them with a few incentivized small experiments. Such tests will lead to better chances for us to study how individual-level mental differences impact economic decision making and outcomes.

# Conclusion

Behavioral decision making frameworks on sustainable development related topics is novel yet crucial. In my research, I apply this interdisciplinary setup to analyze the determinants of various issues relevant for sustainable development – in this dissertation, epidemiological response for COVID-19 and individual decisions in the developing world. To sum up, such a framework involves incorporating three branches of behavioral decision making (BDM) perspectives together to analyze the decision structures of a certain problem.

In my analysis, I would look at three aspects of a development related decision problem. Typically, economic incentive structures determine the "rational" part of decisions, setting up the basic pros and cons of a choice, such as whether going out to work during COVID-19 is highly dependent on economic vulnerability. Even for Trump support, or anti-intellectual beliefs about climate change, economic incentives strongly matter: voters keen in campaigning against climate change may have high reliance on traditional fossil fuel sectors. Despite the importance of economic incentives, they cannot fully explain the large variances of behaviors for people with similar economic needs in many cases. Sometimes, people are showing "behavioral economic" patterns and deviate from economic rationality; sometimes, people tend to let their values, self-consciousness, political affiliation or other psychological forces drive their decisions, rather than "economic" incentives, and sometimes, intrinsic personality traits or preferences determine their choice and destiny. And finally, both branches of drivers might be moderated by social contexts, or nudged by certain interventions (Michie et al. 2011; Thaler and Sunstein 2009). The exploration of and dynamics of the three sides is associated with various fundamental questions, such as (1) which side is dominant in shaping behaviors in a certain scenario? and (2) how to better intervene behaviors with the knowledge of relative strength of predictors?

Answering these questions requires coalition of different fields, forming three "sides" of the triangle. In the first chapter, we look at all three sides. The main setup of this paper is focusing on the left side: economic vulnerability and partisanship are the two major determinants for social distancing and masks, and the relative strength leads to difference in marginal impacts. In addition, this paper discusses (although not fully tests) how contexts may moderate the process. For instance, asymmetric information exposure, motivated thinking or scarcity mindset (usually caused by EV) may interact with these two drivers during the pandemic, worsening the compliance to COVID-19 response. In the second chapter, the stories are similar but in this case, the "context" of interest is social reinforcement. On the whole picture, local EV, partisanship and social reinforcement match the framework of the triangle, and it is valuable to incorporate them quantitatively in one framework. In the last chapter, however, we switch to another form of the triangle. We look at individual differences and how it is determined across cultures and economies. The major implication of this research for sustainable development lies in the key differences we find: in the developing world, many psychological findings in "WEIRD" countries might not apply. This, along with the increasing concern on mental health in developing countries, will shed important light on relevant research and practice.

Thus, despite the differences of topics I investigate across these chapters, they are coherent in one key topic: using an interdisciplinary, "triangular" framework to study the determinants or predictors of human behaviors related to sustainable development. It emphasizes the complexity of decisions making. This framework could be implemented in various hotspot in current sustainability science: climate change, poverty reduction, epidemic response, and natural disaster mitigation. This dissertation thereby calls for similar research on more "explicit" sustainable development topics and has various policy implications. In real-world policy making, it is typical that micro-level decision entities tend to be affected by many aspects of incentives and motivations. If we only take part of them, the effectiveness would be highly aggravated, as discussed in the literature that links behavioral science to sustainability and poverty reduction (Duflo and Banerjee 2011; Mullainathan and Shafir 2013).

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# Appendix A: Supplementary Materials for Chapter 1

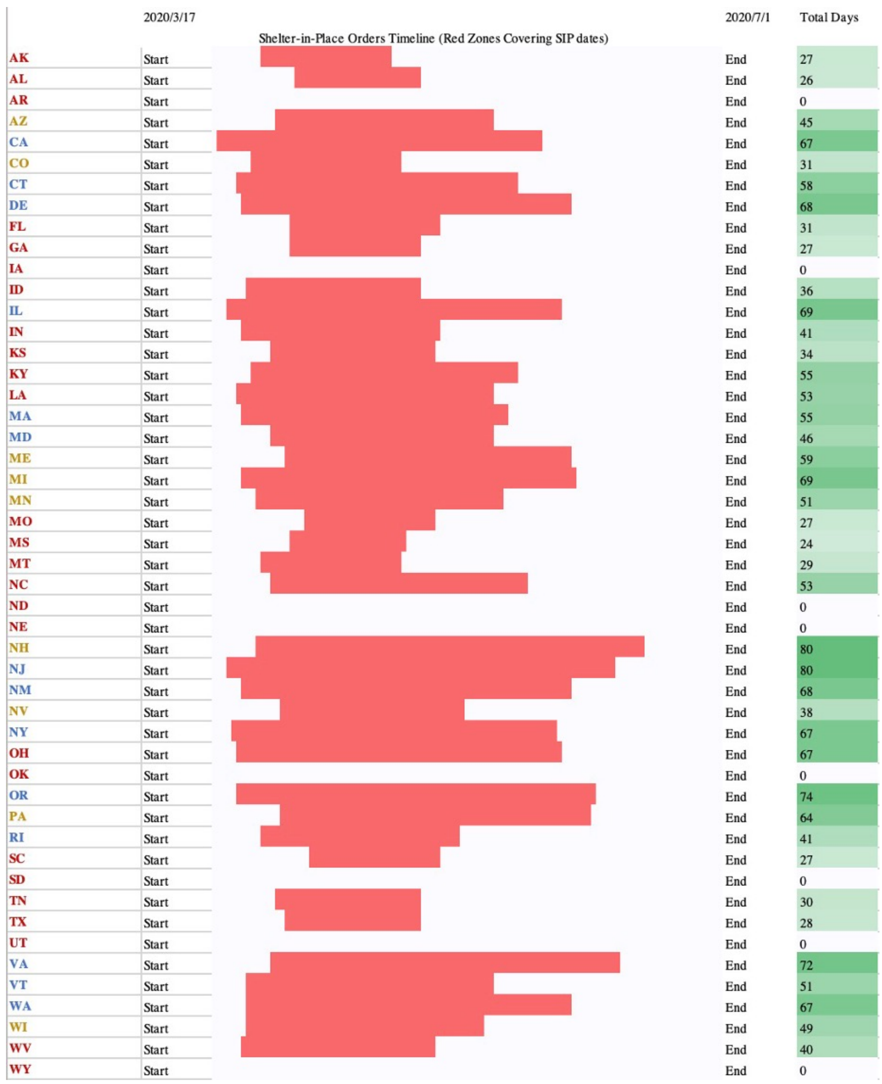


Figure A.1: Comparison of COVID-19 Policies Across Different Regions in the United States

Note: The color of the state is based on the coding of the second chapter. A state is classified as Democratic (colored in blue), Republican (colored in red), or swing (colored in yellow): a state is Democratic (Republican) if it has two Democratic (Republican) senators at least 48% of the vote was for Clinton (Trump) in 2016, or if it has one Democratic (Republican) senator and at least 50% of the vote was for Clinton (Trump) in 2016. The remainder are swing states.

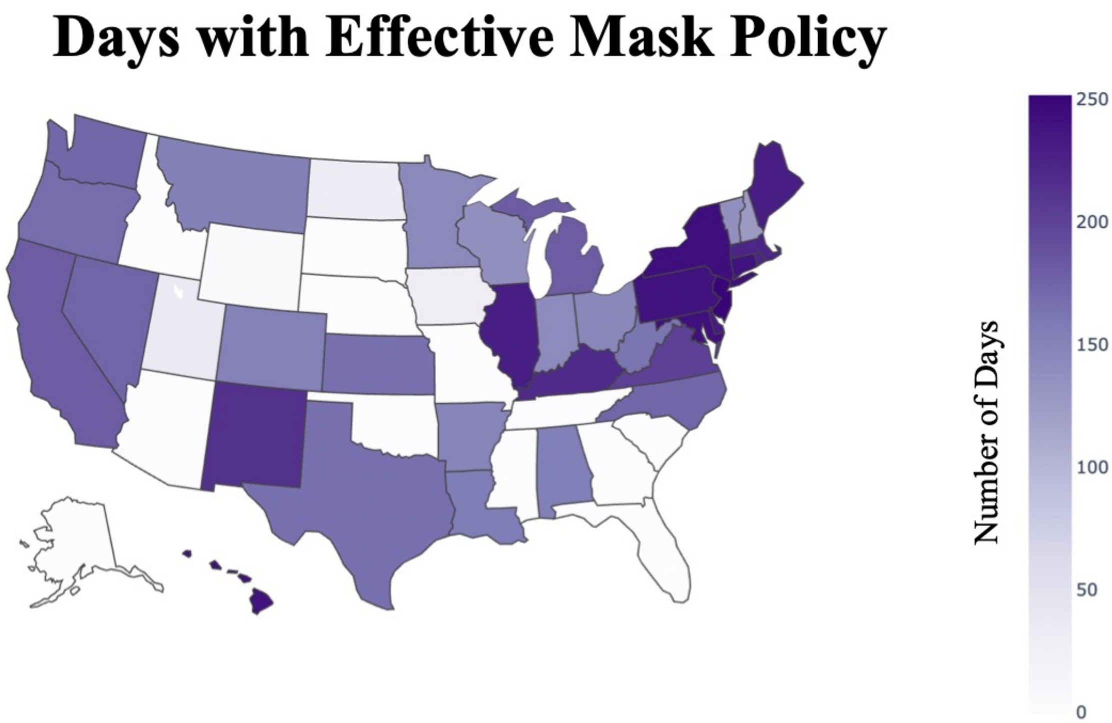


Figure A.2: Mask Mandates Timeline

Note: Mask mandate coverage time length as to December 15, 2020. (No states have yet revoked a mask mandate after launching one in 2020.)
More details could be seen in https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

| | | Obs. | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|---|
| Time Spent-Workplace | Total | 2746 | -25.05 | 6.47 | -59.75 | -0.74 |
| | Mar-Jul | 2746 | -27.78 | 6.59 | -60.92 | -13.73 |
| | Aug-Nov | 2723 | -20.51 | 6.95 | -58.52 | 18.73 |
| Time Spent-Home | Total | 1750 | 7.16 | 3.34 | -1.94 | 23.76 |
| | Mar-Jul | 1381 | 10.34 | 3.18 | 1.01 | 26.06 |
| | Aug-Nov | 1750 | 5.68 | 2.54 | -2.60 | 20.62 |
| Time Spent-Grocery/Pharmacy | Total | 1607 | 2.26 | 11.27 | -45.33 | 87.58 |
| | Mar-Jul | 1598 | 2.94 | 11.84 | -45.33 | 78.05 |
| | Aug-Nov | 1607 | -2.64 | 9.56 | -56.90 | 54.76 |
| Time Spent-Restaurants | Total | 2433 | 281.00 | 272.93 | 0.00 | 4528.92 |
| | Mar-Jul | 2421 | 254.02 | 301.37 | 1.44 | 9257.35 |
| | Aug-Nov | 2432 | 321.13 | 307.17 | 0.00 | 4321.85 |
| Mask Coverage | July 2-July 17 | 3088 | 0.74 | 0.10 | 0.36 | 0.96 |
| | Sep-Nov | 629 | 88.13 | 5.66 | 68.11 | 97.95 |

Table A.1: Summary Statistics of Dependent Variables at the County Level

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Total Population | 3,088 | 101256 | 323565 | 82 | 9818605 |
| Poverty Rate (percentage) | 3,088 | 15.46 | 6.32 | 0.00 | 50.60 |
| Median Household Income 2017 | 3,088 | 50908 | 13275 | 22679 | 136191 |
| Uninsured Population Percentage | 3,088 | 0.18 | 0.05 | 0.03 | 0.39 |
| Bachelor's Degree Percentage | 3,088 | 18.87 | 8.50 | 3.70 | 70.10 |
| Gini Coefficient | 3,088 | 0.43 | 0.04 | 0.21 | 0.65 |
| Indicator of Ruralness | 3,088 | 5.25 | 3.47 | 1.00 | 12.00 |
| Agricultural as %of GDP | 3,088 | 2.13 | 2.59 | 0.00 | 29.25 |
| Work-from-home percentage | 3,086 | 0.27 | 0.04 | 0.00 | 0.50 |
| Unemployment in 2010 | 3,088 | 9.36 | 3.15 | 2.10 | 28.80 |
| Trump Vote in 2016 | 3,088 | 63.84 | 15.43 | 4.12 | 95.27 |
| Evangelicals/1000 people | 2,791 | 232.14 | 157.47 | 2.85 | 987.83 |
| Catholics/1000 people | 2,661 | 125.88 | 129.41 | 0.00 | 999.57 |
| Religious Diversity | 3,088 | 0.97 | 0.26 | 0.00 | 1.67 |
| Belief in Climate Change | 3,088 | 64.74 | 5.89 | 48.94 | 86.53 |
| White population percentage | 3,088 | 79.18 | 19.26 | 2.50 | 99.20 |
| Latino population percentage | 3,088 | 7.91 | 12.97 | 0.00 | 97.15 |
| Male Population percentage | 3,088 | 0.50 | 0.02 | 0.41 | 0.79 |

Table A.2: Summary Statistics of Independent Variables at the County Level

Note: the county-level average of work-from-home is much lower than the national average because more populous counties tend to have more people who can work from home yet count only once.

| | Time Spent | | | | Mask Wearing | | Cases | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Workplace | Home | Groceries | Restaurants | July 2-July 17 | Oct - Nov | Mar 1-May 1 | May 1-Sep 15 | Sep 15-Nov 30 | Mar 1-Nov 30 |
| Total Population | -0.407 | 0.435 | -0.274 | -0.047 | 0.285 | 0.313 | 0.144 | 0.065 | -0.119 | -0.045 |
| Poverty Rate (percentage) | 0.143 | -0.320 | 0.015 | 0.024 | -0.041 | -0.002 | 0.008 | 0.364 | -0.121 | 0.082 |
| Median Household Income | -0.500 | 0.660 | -0.257 | -0.061 | 0.284 | 0.309 | 0.115 | -0.182 | 0.017 | -0.058 |
| Uninsured Population % | 0.136 | -0.242 | -0.097 | 0.059 | 0.007 | -0.210 | -0.028 | 0.331 | -0.225 | -0.030 |
| Bachelor's Degree % | -0.608 | 0.696 | -0.318 | -0.015 | 0.353 | 0.491 | 0.091 | -0.133 | -0.054 | -0.099 |
| Gini Coefficient | -0.121 | 0.093 | -0.186 | 0.069 | 0.137 | 0.255 | 0.086 | 0.273 | -0.146 | 0.027 |
| Indicator of Ruralness | 0.400 | -0.519 | 0.277 | -0.102 | -0.456 | -0.211 | -0.157 | -0.116 | 0.278 | 0.153 |
| Agricultural as %of GDP | 0.210 | -0.271 | 0.031 | -0.147 | -0.211 | -0.060 | -0.082 | 0.041 | 0.111 | 0.102 |
| Work-from-home % | -0.421 | 0.549 | -0.361 | -0.062 | 0.071 | 0.461 | 0.084 | -0.032 | 0.099 | 0.083 |
| Unemployment in 2010 | 0.116 | -0.254 | 0.103 | -0.009 | 0.226 | -0.072 | 0.020 | 0.158 | -0.388 | -0.249 |
| Trump Vote in 2016 | 0.537 | -0.611 | 0.345 | 0.166 | -0.502 | -0.774 | -0.198 | -0.133 | 0.194 | 0.066 |
| Evangelicals/1000 people | 0.262 | -0.337 | 0.061 | 0.309 | -0.239 | -0.446 | -0.083 | 0.262 | -0.037 | 0.094 |
| Catholics/1000 people | -0.224 | 0.324 | -0.149 | -0.197 | 0.191 | 0.380 | 0.169 | -0.044 | 0.162 | 0.137 |
| Religious Diversity | -0.222 | 0.315 | -0.149 | -0.092 | 0.216 | 0.206 | 0.048 | -0.060 | 0.012 | -0.012 |
| Belief in Climate Change | -0.531 | 0.622 | -0.370 | -0.173 | 0.501 | 0.716 | 0.190 | 0.084 | -0.186 | -0.085 |
| White population % | 0.282 | -0.341 | 0.402 | 0.028 | -0.364 | -0.344 | -0.188 | -0.512 | 0.241 | -0.084 |
| Latino population % | -0.203 | 0.263 | -0.318 | -0.095 | 0.303 | 0.221 | 0.055 | 0.238 | -0.097 | 0.046 |
| Male Population % | 0.087 | -0.135 | 0.034 | -0.117 | -0.073 | -0.210 | 0.019 | 0.084 | 0.136 | 0.162 |

Table A.3: Simple Pairwise Correlation – Cases/Response with Independent Variables

Note: In our main text, we carefully documented how economic vulnerability and American Conservatism predicts the failure of social distancing and mask coverage. Based upon our good knowledge of the causality between these two measures and COVID-19 spread, we would believe that EV and Conservatism are very likely to be contributors to COVID-19 spread and the red-drift of epicenters in the US. However, the main text does not include direct quantification of how COVID-19 cases are determined by economic vulnerability and American conservatism except for an aggregated demonstration at the state level. In the supplementary materials, we are providing a dynamic mediating model on this effect.

| | |
|---|---|
| Dependent Variables | Cases increment T+2 |
| Lagged Dependent Variables | Cases increment T+1 |
| Endogenous Variables | COVID Response |
| Exogenous Variables | EV, conservatism, cases increment T-1/T-2, controls, fixed effects |

Table A.4: Variable Setup of Instrumental Variable Regressions

Note: we use the results in the main body as the first stage of the IV regressions. For the second stages, we demonstrate the first-glance results in a graph and show the computed results in Table S12A and S12B.

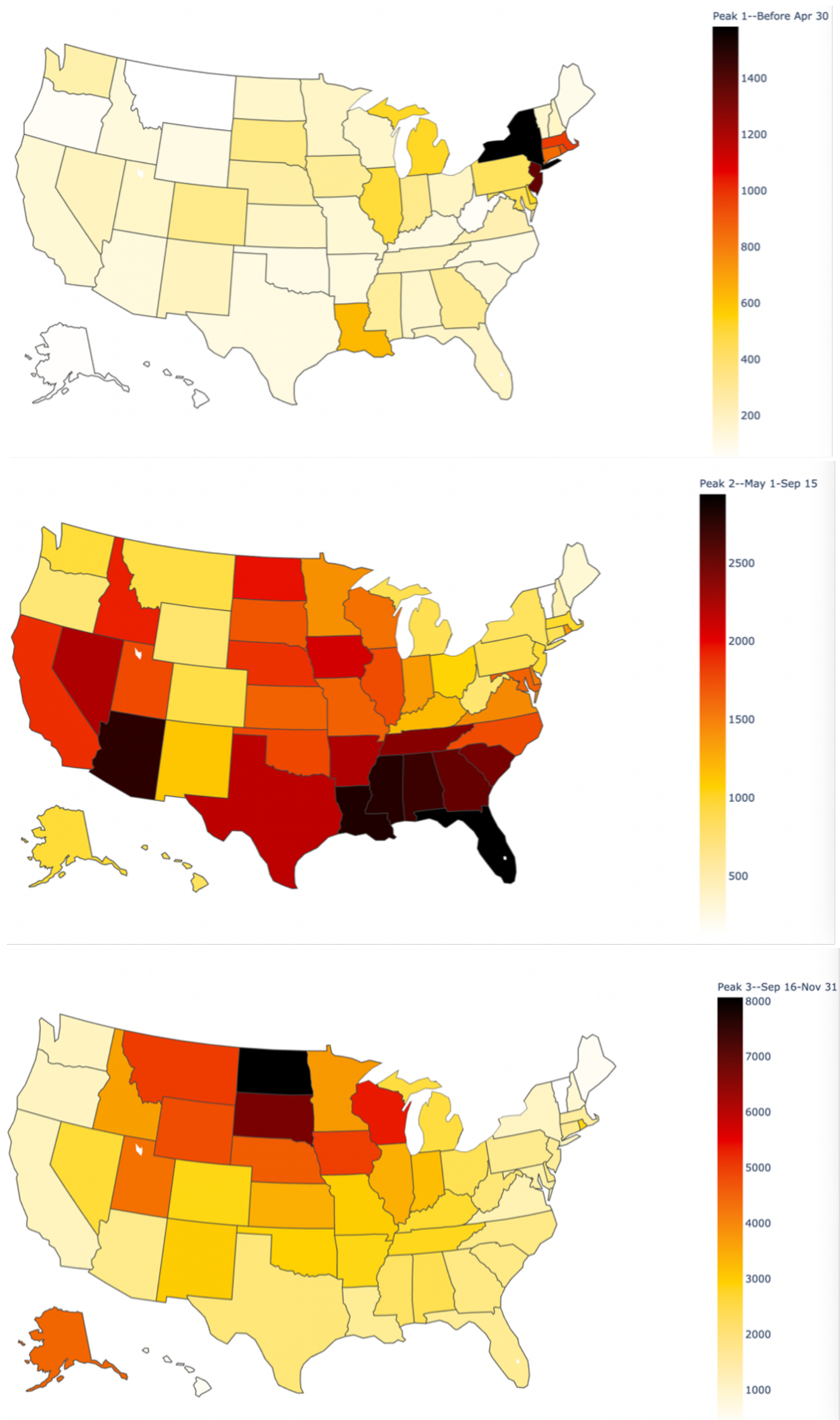


Figure A.3: Regional Epicenter Dynamics of COVID-19 from March to November in the USA (Unit: Confirmed Cases/100,000 Residents)

Note: the three graphs are relatively Cases/100,000 Residents Before Apr 30, May 1-Sep 15 and Sep 16-Nov 31.


Figure A.4: Economic Vulnerability Distribution across US States

Note: Our measures include: Poverty Rate, Unemployment Insurance Amount, Nest Egg Index and Uninsured Population, Tele-workable Population (Wage Adjusted) and Dependency Ratio (Working population/Young and Elder Population), Technology Index, and Agricultural Percentage of GDP.

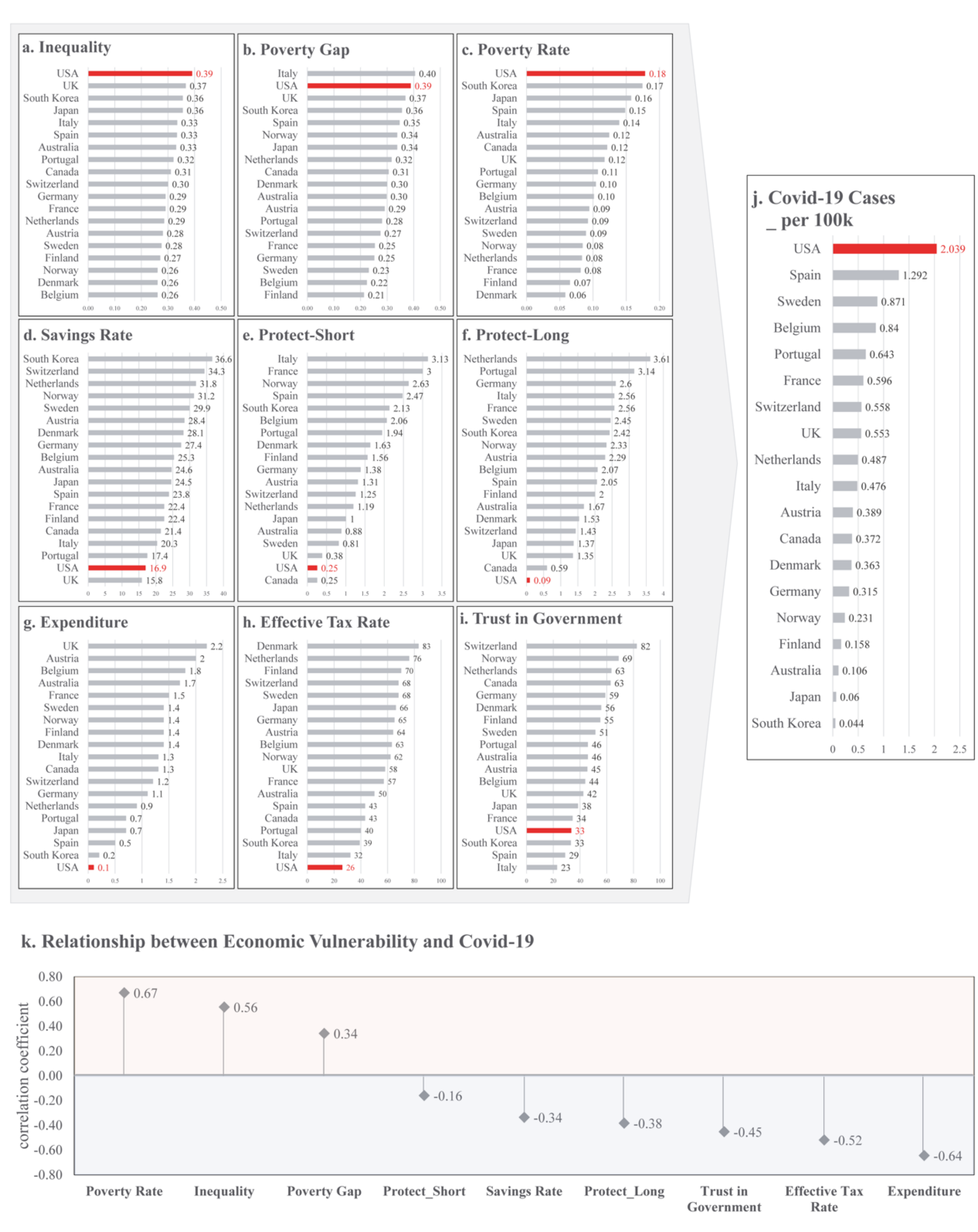


Figure A.5: Important Economic Vulnerability Indicators Across Developed OECD Countries and Their Correlations with Infections

Note: Time period is May 1-Sep 15, which was the second peak in the United States but a relatively low-infection period in other developed countries

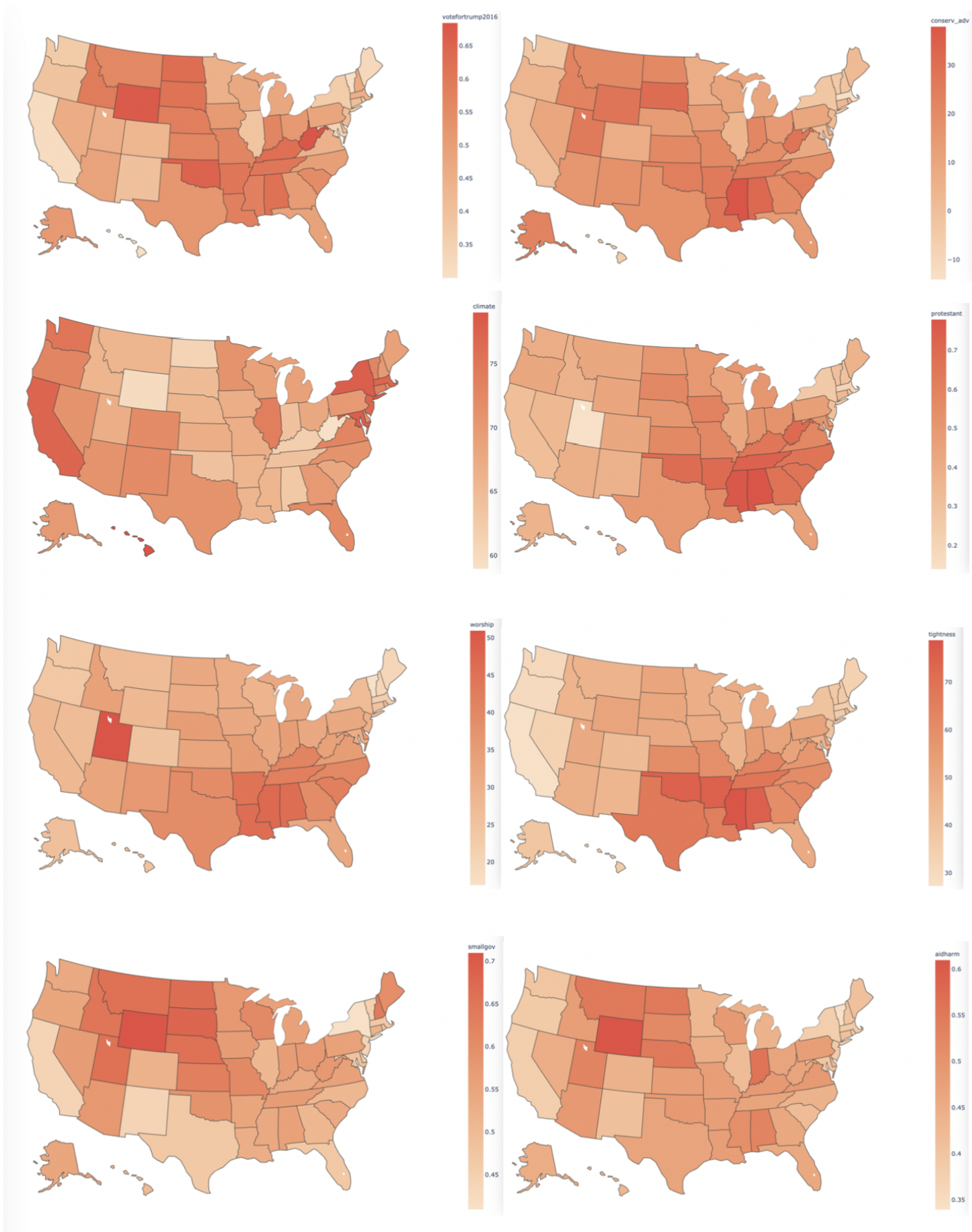


Figure A.6: Ideology acorss States

Note: The variables are respectively Trump Share in 2016 Elections, Conservative Advantage, Belief in Climate Change, Protestant Population, Proportion of People Joining Religious Activities Weekly, Tightness-Looseness, Preference for a Small Government and Belief that Government Aid is Harmful

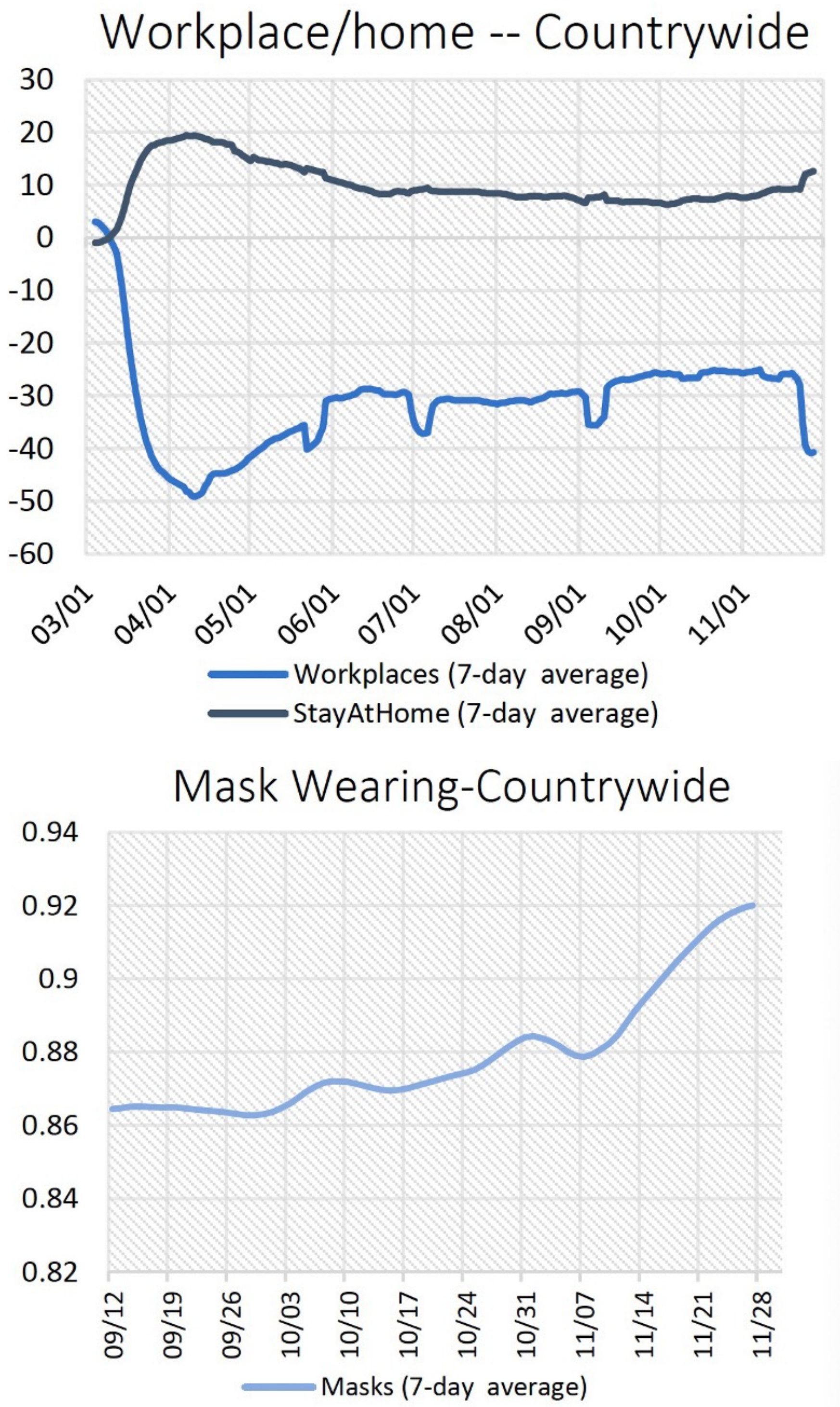


Figure A.7: Mobility (Top) and Mask Wearing (Bottom) over Time across the US

Note: the unit of the Y-axis is the relative increase/decrease in comparison to the same time period in 2019.

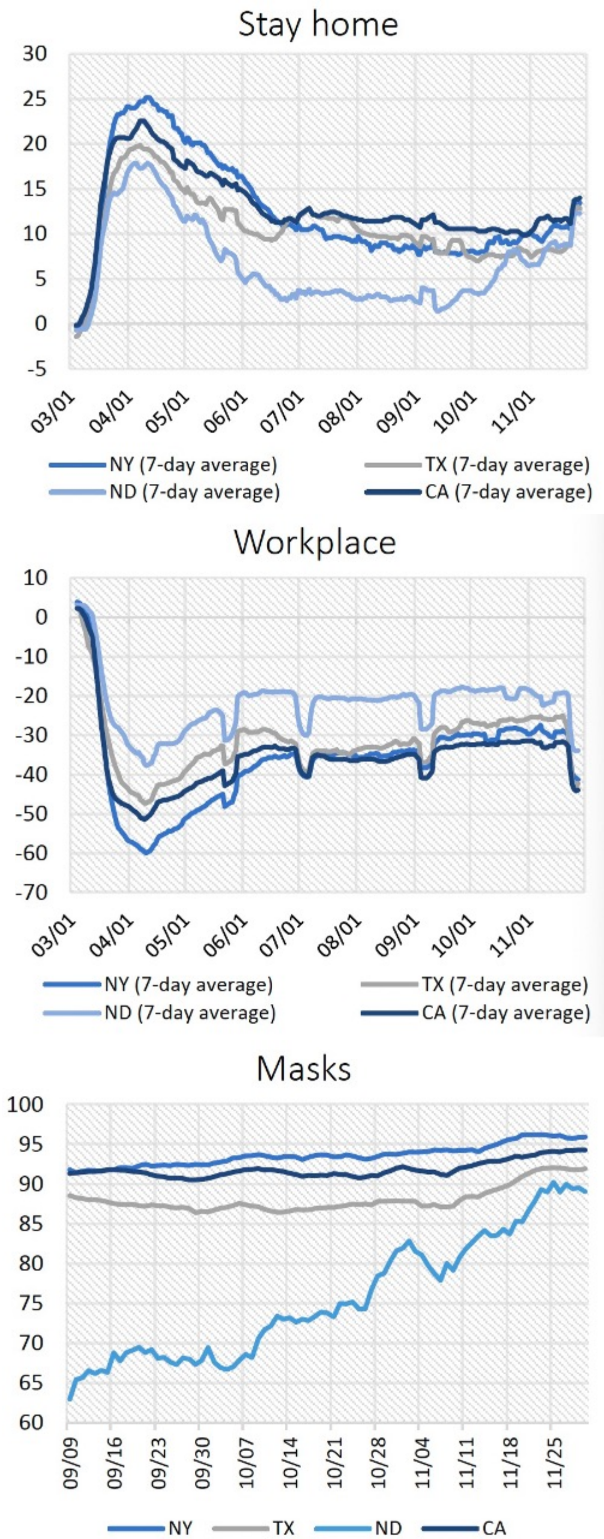


Figure A.8: Time Dynamics of Mobility, Mask Wearing and Confirmed Cases/100,000 in Representative States of the Three Peaks

Note: the unit of the Y-axis is the relative increase/decrease in comparison to the same time period in 2019.

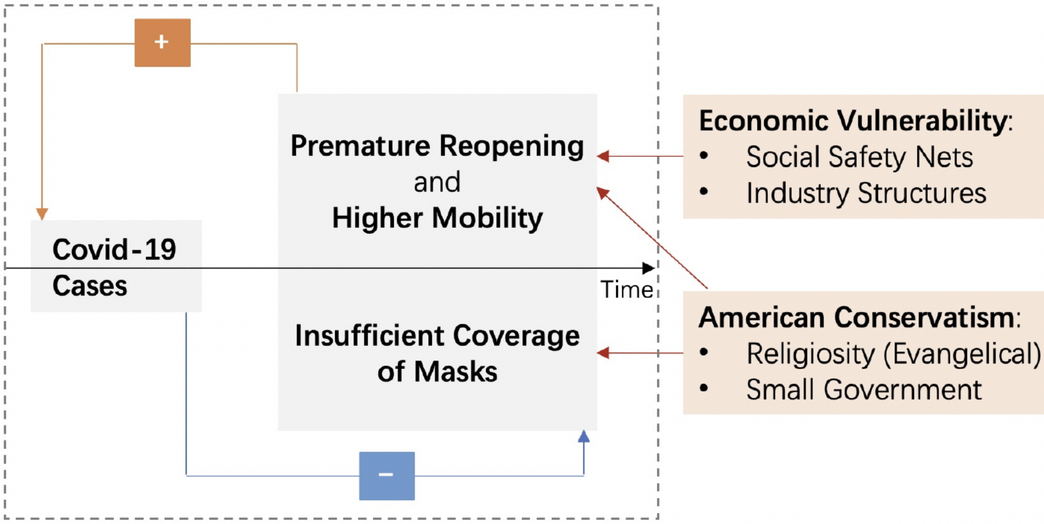


Figure A.9: A Demonstration of Feedback Loops of COVID-19 Spread

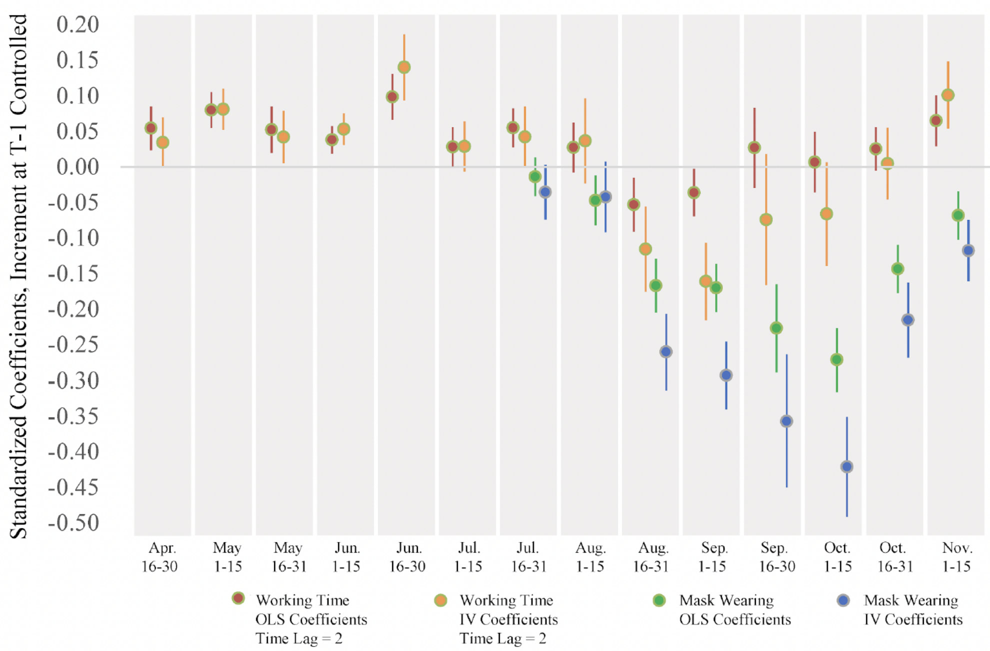


Figure A.10: Regression Coefficients of Working Time and Mask Coverage on Case Increments

Note: This is a coefficient plot of the second stage regression. Notations – Left hand side: case increment (new cases) within the time span t, which is mentioned on the X axis. Right hand side: case increment (new cases) within the time span t-1, one term earlier than the left hand side and COVID-19 response measures (time spent in workplaces, and mask wearing within time span t-2. In OLS, regressions were conducted as mentioned above. In IV, workplace time and mask wearing were instrumented by political, ideological variables and other controls.

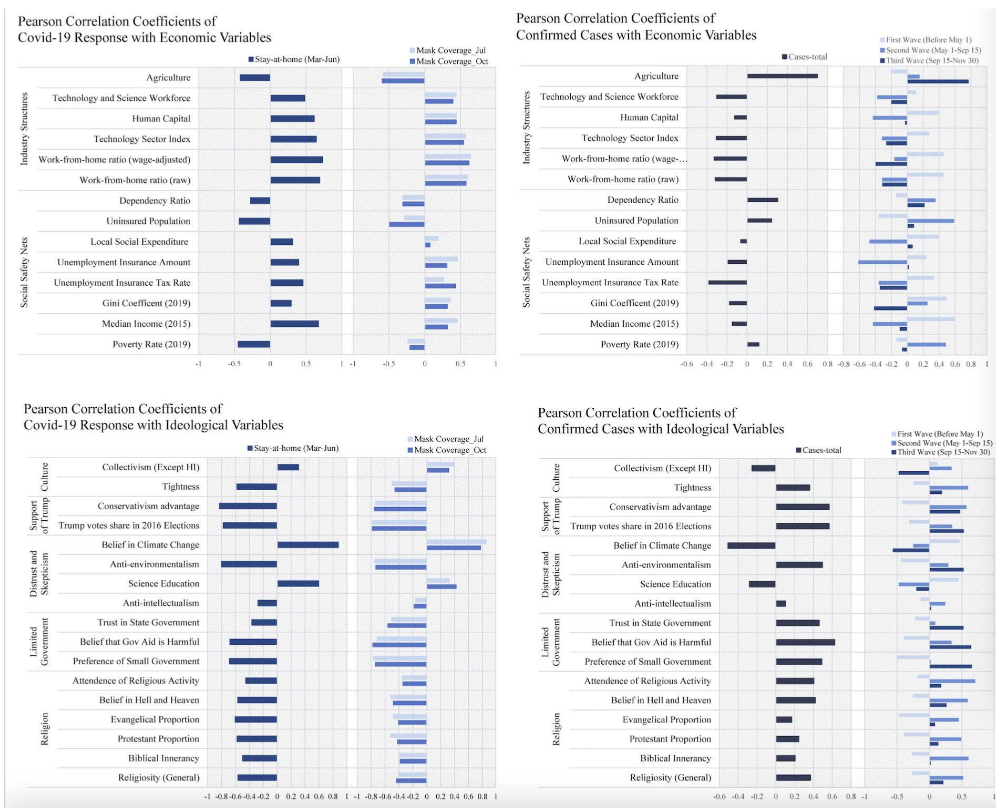


Figure A.11: Pearson Correlation Coefficients of COVID-19 Response and Confirmed Cases / 100K with Economic and Ideological Variables

# Appendix B: Supplementary Materials for Chapter 2

## B.1 New Case Effects

In the main body of this paper, we discussed the part of social reinforcement on policy implementation and justify our major claim. In the supplementary material, we use a contrasting to show that such reinforcement seems to have a larger predictive power than severity in determining the response, which is another important piece of side evidence supporting our study. The goal of this subsection is to look at the impact of the number of new cases in a state on the probability of implementing a mask-wearing policy. We do this by looking at the probability of adopting as a function of the number of new cases and the percentage of democratic or republican states with mask-wearing policies: these results are contained in Figure B.1. In these figures the horizontal axes are the number of new cases and the percentage of republican states with mask-wearing policies, the vertical axis is the probability of a democratic state without such a policy implementing one, and each diagram corresponds to a different fraction of democratic states with policies - these percentages are 0%, 50%, 62.5% and 93%.

The figures show that there is essentially no impact of the number of new cases on the probability of a democratic state adopting a mask-wearing policy, which is consistent with the coefficients on $NC$ in Table 2.1: these coefficients are never significant. This is different from the position with SIP policies shown in Figure B.3 below, where the impact of case numbers is more significant.

Figure B.2 presents the same analysis for republican states: they show that for low values of the republican mask rate and high value of the democratic rate, there is sensitivity of the probability of a republican state choosing a mask policy, but otherwise it has no effect. This is similar to the situation shown in Figure B.4 for republican states deciding whether to introduce an

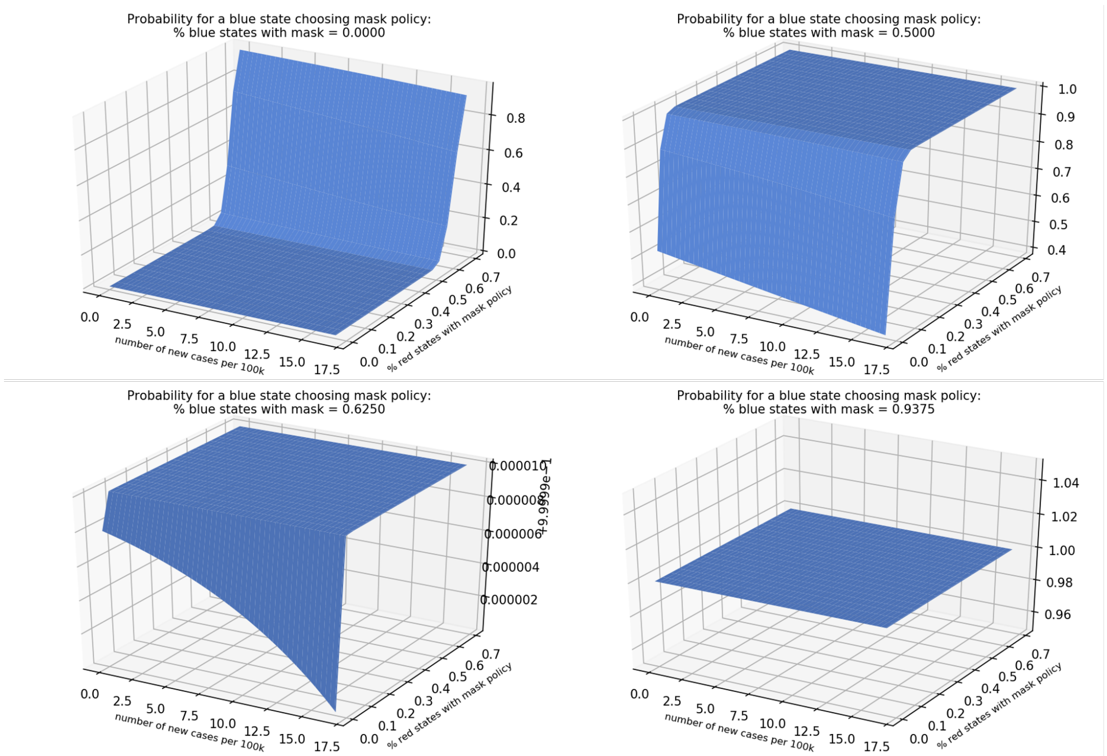


Figure B.1: Effect of New Cases on Democratic Mask Choice

SIP policy.

The next step in our analysis is to investigate the effect of the number of new cases of COVID-19 in a state on the probability of its adopting an SIP policy. We do this by looking at the probability of adopting as a function of the number of new cases and the percentage of democratic or republican states with SIP policies: these results are contained in Figure B.3 In this figure the horizontal axes are the number of new cases and the percentage of republican states with SIP policies, the vertical axis is the probability of a democratic state without a policy implementing one, and each diagram corresponds to a different fraction of democratic states with SIP policies - these percentages are 0%, 31%, 56% and 93%.

What these figures demonstrate very clearly is that a change in the number of new cases in a democratic state has little impact on the probability of that state choosing an SIP policy, except when the percentage of democratic states with an SIP policy is already high (last figure) and the percentage of republican states is low. The selection of an SIP policy appears to be driven more by

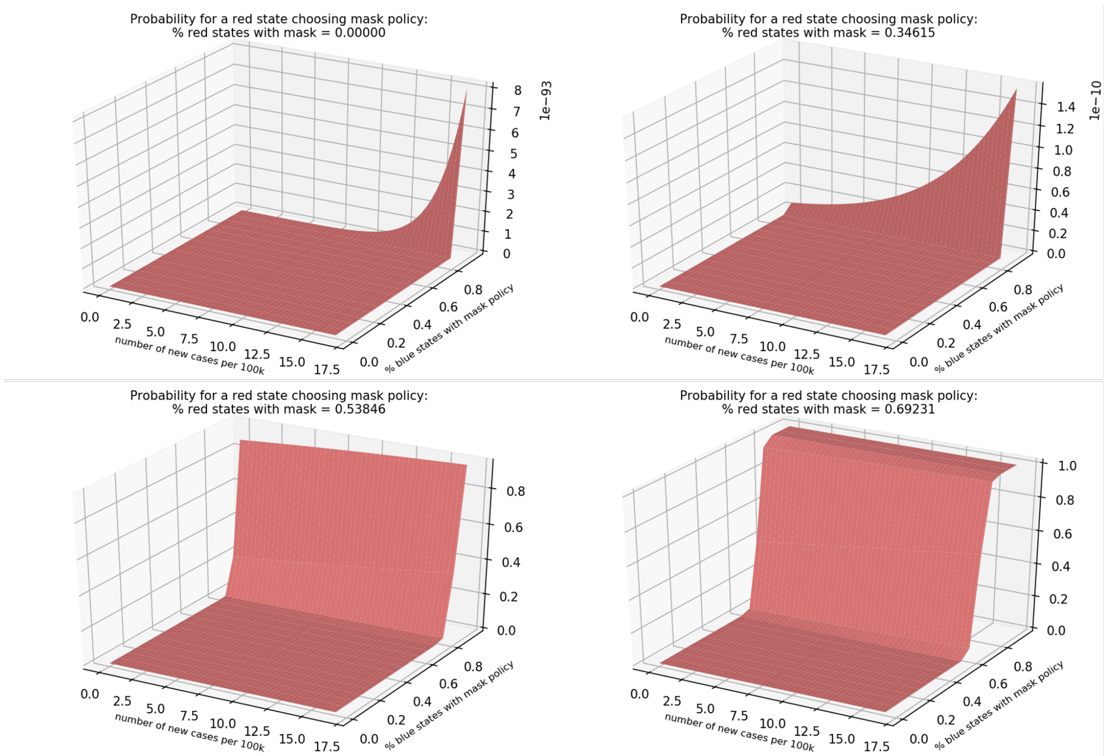


Figure B.2: Effect of New Cases on Democratic Mask Choice

social and political reinforcement rather than by a focus on the basic facts of public health.

Much the same is true for republican states. Figure B.4 illustrates this: the interpretation is the same as for democratic states. What we see in this case is that for high values of the percentage of blue states with SIP policies and low values of the percentage of red states with such policies, an increase in the number of cases in a republican state will increase the probability of the remaining republican states choosing an SIP policy.

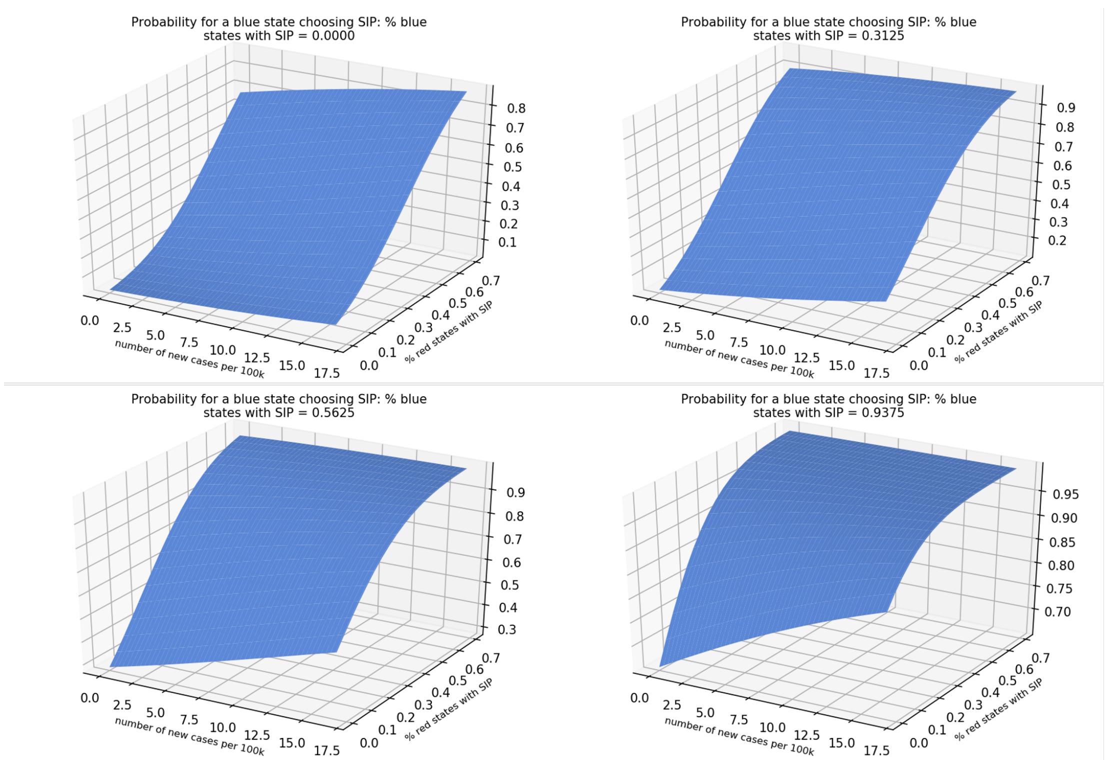


Figure B.3: Effect of New Cases on Democratic SIP choice

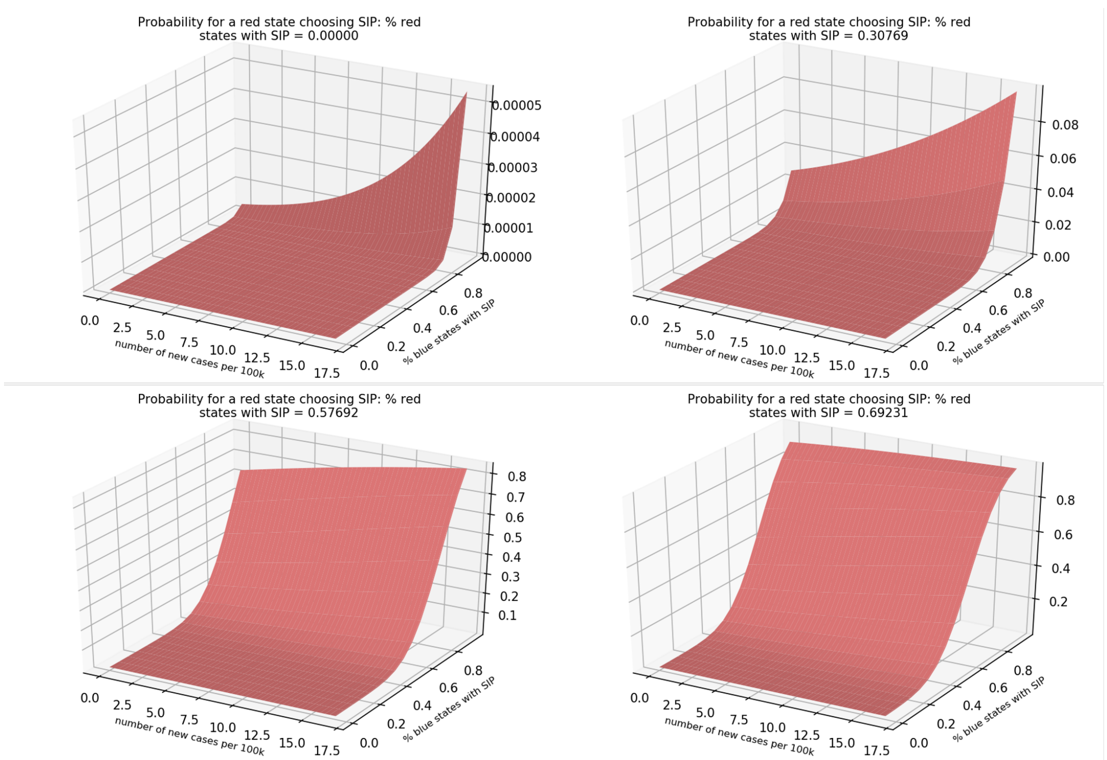


Figure B.4: Effect of New Cases on Republican SIP choice

## B.2 Robustness Checks

In this section we present results which enable us to assess the robustness of the material presented above. We approach the same questions by different methods.

### B.2.1 Linear Regressions

Another alternative that we have investigated is the use of linear regressions rather than discrete choice models, with the dependent variable now the fraction $F$ of days within a specified time window that a state had a mask-wearing or SIP policy in place. We look at three time windows - one day, seven days and fourteen days. In the seven day case, the dependent variable for state $j$ is the fraction of the days in that seven day interval in which state $j$ has the policy in place, denoted $F_{policy,j,t,}$ where *policy* may be either *mask* or *SIP*. As independent variables we have for mask-wearing $Mask_{blueate,t}$, $Mask_{redrate,t}$, $Mask_{swingrate,t}$ where $t$ denotes the time interval (one, seven or fourteen days) $Mask_{bluerate,t}$ is calculated for a seven day interval as follows.

$$Mask_{bluerate,t} = \frac{\sum_{bluestates} (\#days\ state\ has\ policy)}{\#bluestates * 7}$$

and the other dependent variables are calculated similarly. The estimating equation is now

$$F_{policy,j,t} = \alpha_j Policy_{bluerate,t} + \beta_j Policy_{redrate,t} + \gamma_j Policy_{swingrate,t} + \delta_j C_{j,t} + K + \epsilon_{j,t} \quad \text{(B.1)}$$

where again *policy* may be either *mask* or *SIP*.

We have estimated this equation using as the time interval a single day, seven days and fourteen days. The results are all similar and are shown in tables B.1 and B.2.1.

Table B.1 shows the results of these regressions for mask-wearing policies. Several aspects of these results are worth mentioning. One, as noted, is that the period over which data is aggregated makes no difference: patterns of coefficient significance are the same across all three, and the coefficients are very similar in the three cases. The next point is that they show a very

| | D | R | D | R | D | R |
|---|---|---|---|---|---|---|
| Period, days | 1 | | 7 | | 14 | |
| Dem mask rate | 0.907*** | −0.112 | 0.930*** | −0.141 | 0.944*** | −0.188 |
| Swing mask rate | 0.29 | 0.598*** | 0.291 | 0.676*** | 0.287 | 0.828*** |
| Rep mask rate | −0.233 | 0.119 | −0.256 | 0.016 | −0.262 | −0.18 |
| New cases/100k | 0.0035 | 0.00074 | 0.00055 | 0.00055 | 0.00031 | 0.0000 |
| Const | −0.0043 | −0.025 | −0.022 | −0.022 | −0.034 | −0.0183 |

Table B.1: Robustness for Masks: Change of the Time Window

Note: Dependent variable is the fraction of the days in the interval in which state $j$ has a mask policy in place. State-level fixed effects included.

| | D | R | D | R | D | R |
|---|---|---|---|---|---|---|
| Period, days | 1 | | 7 | | 14 | |
| Dem SIP % | 0.819*** | −0.0187 | 0.825*** | −0.412 | 0.851*** | −0.066 |
| Swing SIP % | 0.259 | 0.121 | 0.272 | 0.132 | 0.254 | 0.152 |
| Rep SIP % | −0.055 | 0.872*** | −0.072 | 0.885*** | −0.072 | 0.888*** |
| New cases/100k | 0.0007 | 0.00232 | 0.0000 | 0.00034 | 0.00002 | 0.00004 |
| Const | 0.0122 | −0.0252 | 0.0052 | −0.021 | −0.0008 | −0.008 |

Table B.2: Robustness for Masks: Change of the Time Window

Note: Dependent variable is the fraction of the days in the interval in which state $j$ has an SIP policy in place. State-level fixed effects included.

robust effect of democratic mask-rates on the choices of democratic states. This is entirely consistent with the logit and probit results in Table 2.1, which are reinforced by Table 2.2 and Figure 2.1. The significance of the coefficient on swing states for republican choices is also consistent with the discrete choice results in Table 2.1. However the absence of a significant positive coefficient on the republican mask rate is inconsistent with the earlier results as shown in Table 2.1, though it is consistent with the figure - which is itself at variance with Table 2.1, except in regions of the state space where the mask rates of democratic and swing states are both high.

Table B.2.1 shows the analogous results for SIP policies. Democratic states show a significant positive constant on the democratic policy rate, as do republican states on the republican rate. The results are completely consistent across the differing time periods (the key entries in the table are underlined, and are (dem on dem) 0.819, 0.825 and 0.851: (rep on rep) 0.872, 0.885 and

0.888.) The coefficients on new cases are never significant. These results are consistent with those shown in Table 2.4 and Figures 2.3 through B.4, although Table 2.4 does suggest more of a role for the SIP rates of states of the opposite political orientation. However the figures make it clear that this is true only for limited regions of the state space.

### B.2.2 Geographical Proximity

We use an approach based on the cultural and geographical proximity of states. Rather than assume the the probability of a state adopting a policy depends on the number of other states that have already done so and their political orientations, we assume that the states that matter most may be those that are near to the undecided state and have a similar political culture. Figure B.5 shows one set of regions that we used. These regions were analyzed in the cultural psychology literature (Vandello and Cohen 1999), who developed an index of individualism/collectivism and argued that states in these regions have similar political cultures. This motivated us to carry out logit and probit regressions classifying states by regions rather than by political orientation. The probability of each state choosing a policy is now expressed as a linear function of the policy rates in each region (i.e. the fraction of states in the region with the relevant policy in place), rather than as before a function of the policy rates of democratic, republican and swing states:

$$\Pi_{i,X,t} = \sum_{j} \alpha_{i,j} N_{j,X,t} + \delta_i C_{i,t} + K + \epsilon_{i,t} \tag{B.2}$$

In this equation, $i$ refers to states and $t$ to the day. $X$ denotes the adoption of either an SIP policy or a mask-wearing policy. $N_{j,X,t}$ denotes the fraction of states in region $j$ that have adopted policy $X$ on day $t$. The results in this case are poor, with few significant coefficients, and it appears that sorting states' by political affiliation rather than culture gives a better explanation of COVID-19 policies.

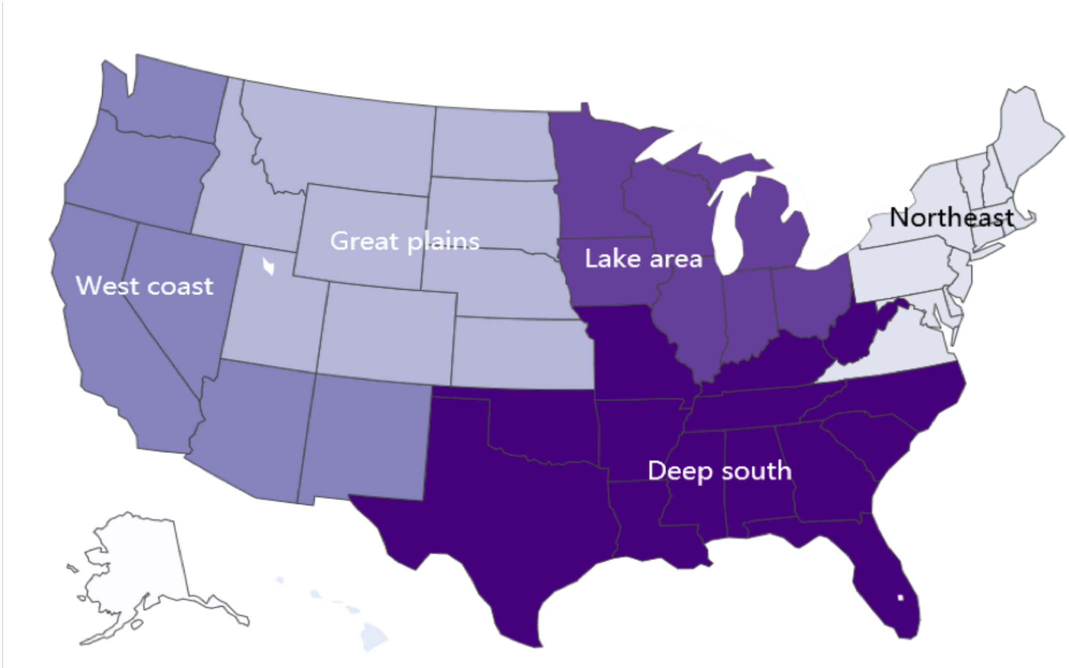


Figure B.5: Cultural and Geographic Proximity (Vandello and Cohen 1999)

### B.2.3 Work-from-home Ratio

In another extension of the analysis we included as an independent variable the fraction of jobs in each state that can be done while the employee is at home - the work from home ratio. We might expect that the Governor of a state would be less willing to implement a shelter-in-place order if most people in the state have to leave home to work: a high value for the work from home ratio suggests a high cost to an SIP order. The data on the work from home ratios comes from Dingel and Neiman (2020). As shown in Table B.3, the work from home ratio does have a negative coefficient in the equation for SIP orders, but in the probit and logit cases it is not significant, and its inclusion does not alter the coefficients of interest.

### B.2.4 Interactions between SIP and Mask Choices

So far we have treated the decisions about introducing SIP and mask policies as separate and independent. In a final check we allow for the possibility that these may in fact influence each other. We therefore re-estimate our main equations (2.7) and (2.5) for the SIP and mask cases

| | Probit | | Logit | |
|---|---|---|---|---|
| | Rep | Dem | Rep | Dem |
| Dem SIP % | $5.736^{***}$ | $2.60^{***}$ | $10.65^{***}$ | $4.324^{***}$ |
| Swing SIP % | $-2.009^{**}$ | $2.793^{***}$ | $-3.679^{**}$ | $5.524^{***}$ |
| Rep SIP % | $8.394^{***}$ | $3.590^{***}$ | $15.23^{***}$ | $8.996^{***}$ |
| NewCase/100K | 0.0375 | $0.0431^{***}$ | 0.0542 | $0.0822^{***}$ |
| WFH ratio | −16.2 | −5.777 | −32.67 | −9.991 |
| Const | −4.521 | −0.911 | −7.701 | −1.979 |
| Insig2u | $2.659^{***}$ | 0.411 | $3.919^{***}$ | $1.817^{***}$ |
| N | 2756 | 1696 | 2756 | 1696 |

Table B.3: Work-from-ratio and Policy

| | Probit | | Logit | |
|---|---|---|---|---|
| | Rep | Dem | Rep | Dem |
| $N_{D,SIP,t}$ | $5.768^{***}$ | $2.364^{***}$ | $10.70^{***}$ | $3.988^{***}$ |
| $N_{S,SIP,t}$ | $-2.031^{**}$ | $3.184^{***}$ | $-3.695^{**}$ | $6.159^{***}$ |
| $N_{R,SIP,t}$ | $8.492^{***}$ | $2.760^{**}$ | $15.25^{***}$ | $7.379^{**}$ |
| $Mask$ | 0.104 | −0.385 | 0.253 | −0.689 |
| $NC_{i,t}$ | 0.0386 | $0.0481^{***}$ | 0.0541 | $0.0895^{***}$ |
| $K$ | $-8.183^{***}$ | $-2.683^{***}$ | $-17.13^{***}$ | $-5.019^{***}$ |

Table B.4: Dependent Variable Probability of SIP Policy

respectively allowing for interactions between these choices. In equation (2.7) estimating the probability of a state introducing an SIP requirement, we introduce an indicator variable that is zero if it has not introduced a mask-wearing requirement and one if it has. Likewise in equation (2.5) estimating the probability of a state introducing a mask-wearing requirement we introduce an indicator variable that is zero if it does not already have an SIP requirement and one if it does. Tables B.4 and B.3 shows the results of these additions.

The coefficients in table B.4 are very similar to those in Table 2.4, which shows the results of the same estimation except that the variable "mask" is not included. The coefficient on "mask" in table B.4 is never significant. So it is reasonable to conclude that the choice of an SIP policy is not influenced by whether or not there is a mask-wearing policy in place.

The coefficients in Table B.3 are again similar to those in Table 2.1 where we estimated the probability of introducing a mask-wearing policy: all coefficients have the same sign and the

| | Probit | | Logit | |
|---|---|---|---|---|
| | Rep | Dem | Rep | Dem |
| $N_{D,M,t}$ | $15.83^{***}$ | $31.96^{***}$ | $36.709^{***}$ | $59.35^{***}$ |
| $N_{S,M,t}$ | $8.621^{**}$ | $27.66^{***}$ | $12.81^{*}$ | $57.86^{***}$ |
| $N_{R,M,t}$ | $23.19^{***}$ | $24.756^{***}$ | $35.85^{***}$ | $85.45^{*}$ |
| $SIP$ | 0.644 | $-2.371^{*}$ | 11.09 | −5.527 |
| $NC_{i,t}$ | 0.209 | −0.0127 | 0.0375 | −0.0193 |
| $K$ | $-25.23^{***}$ | $-24.06^{***}$ | $-55.85^{***}$ | $-39.43^{***}$ |

Table B.5: Dependent Variable Probability of Mask-wearing Policy

pattern of significance is the same. One of the coefficients on the SIP variable is significant, though only at the 5% level. Interestingly, the coefficients on "mask" and "SIP" in both table B.4 and table B.5 are positive for republican states and negative for democratic states: however as they are generally not significant we should not read too much into this.

### B.3 Theoretical Appendix

Under assumption (2.1), there is a minimal tipping set $T$ consisting of less than $I-1$ agents, which will tip the least Nash equilibrium to the greatest Nash equilibrium. Furthermore, any Nash equilibrium with less than $I-1$ SIP or mask-wearing orders can be tipped to the equilibrium with $I$ such orders.

We study the effect on agent $j's$ payoff of changing from no SIP to an SIP (changing from 0 to 1) and how this effect is altered by changes in the strategy choices of another agent $i$. We know by (2.1) that if $i$ switches from 0 to 1 then this will increase the incremental payoff to $j$ from the same switch. Let $S_{-i-j}, 1_i, 0_j$ denote the vector of strategies in which all agents other than $i, j$ are choosing $S_k \in S_{-i-j}$ and $i, j$ are choosing 1 and 0 respectively. ($S_{-i-j}$ is the vector of strategies chosen by all agents other than $i$ and $j$.) Define

$$\Delta_j\left(i=0, S_{-i-j}\right) = U_j\left(S_{-i-j}, 0_i, 1_j\right) - U_j\left(S_{-i-j}, 0_i, 0_j\right) \tag{B.3}$$

and

$$\Delta_j\left(i=1,S_{-i-j}\right)=U_j\left(S_{-i-j},1_i,1_j\right)-U_j\left(S_{-i-j},1_i,0_j\right) \tag{B.4}$$

These are the returns to $j$ from changing from 0 to 1 when $i$ chooses either 0 (first line) or 1 (second line) and everyone else chooses $s_k \in S_{-i-j}$. The difference between these is

$$\Delta_{ij}\left(S_{_{-i-j}}\right)=\Delta_j\left(i=1,S_{-i-j}\right)-\Delta_j\left(i=0,S_{-i-j}\right)\geq 0 \tag{B.5}$$

This is the increase in the return to $j's$ change of strategy as a result of $i's$ change of strategy and from (2.1) we know that this is positive. We focus on equation (B.5) when all agents other than $i$ and $j$ are choosing strategy 0 so as to derive conditions for tipping the Nash equilibrium of all zeros to that of all ones:

$$\Delta_{ij}(0)=\left\{U_j\left(0^{I-2},1_i,1_j\right)-U_j\left(0^{I-2},1_i,0_j\right)\right\}-\left\{U_j\left(0^{I-2},0_i,1_j\right)-U_j\left(0^{I-2},0_i,0_j\right)\right\} \tag{B.6}$$

where $0^{I-2}$ indicates that there are $I-2$ zeros in position other than $i$ and $j$. Consider the following sequence of inequalities, which link the equilibrium with all 0s to that will all 1s in a series of steps in each of which an additional state changes strategy from 0 to 1, and which hold because of (2.1):

$$U_i\left(0^{I-1},1_i\right)-U_i\left(0^{I-1},0_i\right)+\epsilon<U_i\left(0^{I-2},1_1,1_i\right)-U_i\left(0^{I-2},1_1,0_i\right) \tag{B.7}$$

$$U_i\left(0^{I-2},1_1,1_i\right)-U_i\left(0^{I-2},1_1,0_i\right)+\epsilon<U_i\left(0^{I-3},1_1,1_2,1_i\right)-U_i\left(0^{I-3},1_1,1_2,0_i\right)$$

$$U_i\left(1_1,..1_{I-2},0_j,1_i\right)-U_i\left(1_1,..1_{I-2},0_j,0_i\right)+\epsilon<U_i\left(1_1,..1_{I-1},1_i\right)-U_i\left(1_1,..1_{I-1},0_i\right)$$

The first inequality here (B.7) shows that the payoff to state $i$ from a strategy change is raised by at least $\epsilon$ when state 1 also picks strategy 1. The second inequality shows that the payoff to $i$ from the change is again increased by $\epsilon$ when state 2 also changes from 0 to 1. Working back from a typical inequality in this sequence we find that

$$U_i\left(0^{I-k}, 1_1, 1_2, ..., 1_i\right) - U_i\left(0^{I-k}, 1_1, 1_2, ..., 0_i\right) > (k-1)\,\epsilon + U_i\left(0^{I-1}, 1_i\right) - U_i\left(0^{I-1}, 0_i\right)$$

Note that $U_i\left(0^{I-1}, 1_i\right) - U_i\left(0^{I-1}, 0_i\right) < 0$ as the vector of zeros is a Nash equilibrium so zero is a best response. Note also that the last difference in this sequence $U_i\left(1_1, 1_2, ...1_{I-1}, 1_i\right) - U_i\left(1_1, 1_2, ...1_{I-1}, 0_i\right) > 0$ as the vector of all ones is a Nash equilibrium and therefore 1 is a best response. As the sequence of differences starts negative and ends positive it must change sign: there will be a $k < I - 1$ such that $(k-1)\,\epsilon - U_i\left(0^{I-1}, 1_i\right) + U_i\left(0^{I-1}, 0_i\right) > 0$ and the first $k$ states will form a tipping set. To be precise we need $k$ to satisfy

$$(k-1)\,\epsilon > U_i\left(0^{I-1}, 1_i\right) - U_i\left(0^{I-1}, 0_i\right)\ \ \forall i \tag{B.8}$$

In this case each of the other states finds it in its interest to change its strategy from zero to one and the equilibrium of zeros is tipped to that of ones if the first $k$ states all change from zero to one. Equation (B.8) shows a tradeoff between the social reinforcement parameter $\epsilon$ and the size of a tipping set $k$ : the great the social reinforcement (the greater $\epsilon$) the smaller the number $k$ in the tipping set.

Next we turn to the characterization of the greatest and least Nash equilibria of the game $\bar{S}$ and $\underline{S}$, whose existence is assured by the theorem of Topkis (Topkis 1979). *A necessary and sufficient condition for* $\underline{S} = (0, 0, ..., 0)$ *and* $\bar{S} = (1, 1, ..., 1)$ *is that for every agent i, if all other agents have chosen the same strategy s, then that common strategy s is i's best response.*

The proposition is immediate.

In plain English, we have Nash equilibria at all zeros and all ones if it never pays to be the odd-man-out. Theorem B.3 has implications in terms of the structure of agents' utility functions. It requires that $U_i\left(0_i, 1_i\right) - U_i\left(0_i, 0_i\right) < 0$ and $U_i\left(1_i, 1_i\right) - U_i\left(1_i, 0_i\right) > 0$. So the derivative of $i's$ payoff with respect to its strategy depends heavily on the strategy choices of others, to the extent of changing sign if these other strategy choices all change. (1) *There is a Nash equilibrium at which* *all states choose 0. (2) There is a Nash equilibrium at which all states choose 1. (3) There is a Nash equilibrium at which all democratic states choose 1 and all republican states choose 0 (or vice versa). (4) If all states are choosing 0 then there is a tipping set of democratic states that can tip the remaining democratic states to choosing 1 so that the equilibrium is that democratic states choose 1 and republicans choose 0. (5) If all states are choosing 1 then there is a tipping set of republican states that can tip the remaining republican states to choosing 0 so that the equilibrium is that republican states choose 0 and democratic states choose 1.*

The proofs are simple. The payoffs to democratic and republican states from choosing 1 or 0 are

$$1: \ \gamma_D N_D + \alpha_D \gamma_R N_R : \ 0: \ (1-\gamma_D) N_D + \alpha_D (1-\gamma_R) N_R \tag{B.9}$$

$$1: \ \gamma_R N_R + \alpha_R \gamma_D N_D : \ 0: \ (1-\gamma_R) N_R + \alpha_R (1-\gamma_D) N_D \tag{B.10}$$

If all states choose 0 then $\gamma_R = \gamma_D = 0$ so in both cases the payoff to 0 exceeds that to 1. Hence all choosing 0 is a Nash equilibrium. And if all choose 1 then $\gamma_R = \gamma_D = 1$ so that the payoff to 1 exceeds that to 0. These statements are true for all parameter values.

If all democratic and republican states choose 1 and 0 respectively then the payoffs to 1 and 0 for democrats and republicans are:

$$Dem, 1 \ \rightarrow \ N_D \ : \ Dem, 0 \ \rightarrow \ \alpha_D N_R \ : \ Rep, 1 \ \rightarrow \ \alpha N_D \ : \ Rep, 0 \ \rightarrow \ N_R$$

so that we have a Nash equilibrium if and only if

$$N_D \geq \alpha_D N_R \ \& \ N_R \geq \alpha_R N_D \tag{B.11}$$

If we think of $N_D, N_R$ as being roughly the same size and $\alpha_D, \alpha_R$ as less than one half, this condition is generally satisfied.

Now suppose that all states are choosing 0, and look for a set that tips the democrats to 1.

If a fraction $\gamma_D$ change to 1, the payoff to 1 for a democratic state is $\gamma_D N_D$,and the payoff to 0 is $(1-\gamma_D)\,N_D + \alpha_D N_R$ and the fraction $\gamma_D$ forms a tipping set if and only if $\gamma_D \geq \frac{\alpha_D N_D + N_D}{2N_D}$.

Finally suppose that all states choose 1 and look for a set that can tip the republicans to 0. If the fraction of republicans choosing 1 falls from 1 to $\gamma_R < 1$ then the payoff to a republican state from choosing 0 is $(1-\gamma_R)\,N_R$ and from choosing 1 is $\gamma_R N_R + \alpha_R N_D$ so 0 is the equilibrium if and only if $\gamma_R \leq \frac{N_R - \alpha_R N_D}{2N_R}$. Of course, as our specification is symmetric, a group of democratic states could also tip its fellows away from SIP policies, just as a group pf republicans could tip their fellows to SIP policies.